# ONLINE APPENDIX

# "Private provision of social insurance: drug-specific price elasticities and cost sharing in Medicare Part D"

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## A Conceptual model: private provider incentives for drug-specific cost-sharing

Our findings suggest that, unlike public prescription drug plans, private plans vary cost sharing considerably across drugs, setting greater cost-sharing for more elastic drugs. This qualitative relationship appears robust to attempts to address a variety of potential contaminants in what is, in the end, a cross-sectional correlation. Here, we provide additional corroborative support for our analysis by showing that it is not merely an empirical regularity but also one that, at least within the context of the highly stylized theoretical model, is the optimal strategy for a profit maximizing monopolist or duopolist.

The intuition for why a private firm's incentives are aligned with the textbook social optimum is quite simple for the case of a monopoly provider. An insurance contract is essentially a two-part tariff in which the provider can charge both a fixed fee (premium) and a variable price per claim (co-insurance). The optimal strategy for this type of two-part tariff is well-known: a profit maximizing monopolist should set the variable price to maximize consumer surplus, and then extract as much of this surplus as possible via the premium. Thus, the co-insurance design should maximize consumer (and hence social) surplus. While the intuition for the duopoly case is more nuanced, the same forces are in play: the duopolists attempt to maximize consumer surplus through the co-insurance, and then compete with each other for market share via premium setting. We formalize this intuition below.[1]

[1] We have not worked out the case of perfect competition, but we think that the predictions for equilibrium

## Setup

We consider an environment where there exists only one drug. The social marginal cost of producing the drug is $w$, which we normalize to be a unit cost $w = 1$. There exists a mass of individuals, who all have the same probability of a health shock $\lambda$. We assume that the health shock can be completely mitigated if the individual takes the drug. The monetized disutility from the health shock is $x$, which we assume to be homogeneous across individuals.

We assume that the disutility from the untreated health shock is unknown ex ante, and is drawn from a uniform distribution $x \sim U[0, K]$. $K > 1$ is the key parameter that guides the extent of moral hazard (i.e. the price elasticity of demand in our empirical results). If $x > 1$, the individual would purchase the drug even at full cost (of $w = 1$); in this case there is no moral hazard and full insurance is efficient. Once $x < 1$, however, individuals would respond to price, and only purchase the drug if the coverage is generous enough. Thus, the higher is $K$, the more likely it is that $x > 1$, and the less responsive individuals are to the price of the drug.

Individuals are risk averse and have a CARA utility over realized utility $u_i(z) = -exp(-\varphi_i z_i)$, where $z_i$ is the individual's realized utility and $\varphi_i$ is the coefficient of absolute risk aversion. The coefficient is individual-specific and guides the heterogeneity in insurance preferences across individuals. Each individual has the opportunity to purchase an insurance contract. The insurance contract is a pair of premium $\pi$ and out-of-pocket price $p < 1$. The out-of-pocket price is the theoretical analog of the empirical co-insurance rate. The individual's certainty equivalent $V(p; \phi)$ for a contract $(\pi, p)$ equates the utility from paying $V$ with

cost-sharing across drugs of different elasticities are less obvious there, and would likely depend on a variety of modeling assumptions, such as the order of decisions, the rationing of consumers, etc.

certainty to the expected utility from having coverage $p$. In other words, $V$ implicitly solves

$$-exp(-\varphi_i(z_i - V)) = \tag{1}$$
$$-(1-\lambda)exp(-\varphi_i z_i) - \lambda Pr(x > p)exp(-\varphi(z-p)) - \lambda \int_0^p \frac{1}{K} exp(-\varphi_i(z_i - x))dx,$$

where with probability $(1-\lambda)$ individuals do not experience a health shock. With probability $\lambda$ they experience a health shock $x$, and either pay $p$ if the disutility from the health shock is greater than $p$, or pay $x$ if the disutility of the shock is less than $p$. Rearranging terms and simplifying, we obtain:

$$V(p;\varphi_i) = \frac{1}{\varphi_i} \ln \left[ (1-\lambda) + \lambda \Pr(x > p) \exp(\varphi_i p) + \lambda \frac{1}{K} \frac{1}{\varphi_i} (\exp(\varphi_i p) - 1) \right]. \tag{2}$$

Using this framework, no insurance is equivalent to a contract of ($\pi = 0$, $p = 1$). Individual's willingness to pay for a contract that offers co-insurance $p$ is given by the difference between her certainty equivalent for that co-insurance and her certainty equivalent from no insurance:

$$WTP_i(p) = V(1;\varphi_i) - V(p;\varphi_i). \tag{3}$$

Insurer's expected profits from a contract $(\pi, p)$ that is sold to consumer $i$ is:

$$\Pi_i = \pi - \lambda(1-p) \Pr(x > p). \tag{4}$$

That is, the insurer collects the premium $\pi$ and with probability $\lambda$ has to pay $(1-p)$ for the drug if the individual decides to purchase the drug. The latter happens if the realization of the monetized value of the health shock is greater than the out of pocket price $p$, i.e. if $x > p$. Insurer's total profits from selling a contract $(\pi, p)$ is

$$\Pi = \int I(WTP_i(p) > \pi) \Pi_i di, \tag{5}$$

and total welfare from selling $(\pi, p)$ is then:

$$TS = \int I(WTP_i(p) > \pi)(\Pi_i + WTP_i(p) - \pi)di. \tag{6}$$

We now consider several scenarios of market structure to highlight the equilibrium relationship between moral hazard – measured by $K$ – and risk exposure in the contract, measured by the co-insurance rate $p$. A higher $K$ implies lower moral hazard, since it implies a higher chance that the monetized value of the health shock $x$ is greater than the social cost of the drug $w$, and hence the individual would want to purchase the drug regardless of the share of the cost $p$ that she must pay out of pocket. The individual's exposure to risk is increasing in the out-of-pocket price $p$; with $p = 0$ the individual is fully insured against fluctuations in her realized utility resulting from health shocks.

## Relationship between co-insurance and moral hazard

**Social Optimum** We start with a social optimum that demonstrates the classic trade-off between moral hazard and risk protection in an optimal insurance setting. The socially optimal price $p$ maximizes total welfare (defined by equation 6); it is given by the $p$ that solves $\lambda(1-p) = V(1;\varphi_i) - V(p;\varphi_i)$, i.e. that equates the expected cost of coverage with the willingness to pay for insurance. Appendix Figure A2 demonstrates the solution to this problem graphically for a selected set of parameter values. As expected , the social planner sets higher levels of risk protection (lower $p$) in cases where the extent of moral hazard is lower ($K$ is higher).

This results is not specific to our highly stylized setting. As noted in the introduction, it is a classic theoretical result (Feldstein 1973; Besley 1988). It does, however, rely on a key assumption that absent insurance (i.e. with no consumer cost sharing) individuals would purchase the socially optimal amount of drugs. Recent papers have challenged this assumption, noting that the patent system marks up drug prices above social marginal

costs and thus inefficiently reduces unsubsidized drug consumption (Lakadwalla and Sood 2009). In addition, failures of rationality may produce sub-optimal drug purchase decisions (Baicker, Mullainathan, and Schwartzstein 2015). Our analysis of the social optimum also abstracts from the possibility that individuals may have different social welfare weights. If, for example, drugs with higher elasticities of demand tend to be consumed by individuals who are sicker and thus perhaps assigned higher weights in the social planner's objective, this would affect the social optimum; it would not however affect the private firm's optimal cost sharing which depends only on the extent of moral hazard and not on the characteristics of the affected individuals.

**Private monopoly** Consider now the case of a monopolist insurer. In this case, the monopolist sets price $p$ that maximizes profits, given by equation (5). We solve this problem numerically for a range of parameter values; Appendix Table A3 reports the results. Comparing the results across different values of $K$, we see that the optimal level of cost sharing $p$ decreases with $K$. That is, the monopolist offers more risk protection in cases that have less moral hazard, which is qualitatively similar to the direction by which $p$ would change with $K$ in the social optimum. The intuition is simple and well understood. Demand is decreasing in both the price of insurance $\pi$ and the cost sharing rate $p$. Comparing increases in $\pi$ and in $p$ that would result in the same increase of expected profits, the latter would raise risk exposure, and thus would lead to a greater demand response by risk averse individuals. This means that the monopolist would optimally set $p$ at its socially efficient level, and then set premium to maximize profits. While this sharp result is driven by our assumption that moral hazard is homogeneous and is not correlated with risk aversion, the overall qualitative intuition is more general.

**Private duopoly** In the duopoly problem, each insurer sets premiums and prices $(\pi, p)$ in a Nash equilibrium. To avoid boundary cases, we assume that each insurer is a monopolist against a fraction $\kappa < 0.5$ of the people, and competes for the remaining $1 - 2\kappa$ share of the

market. If the other firm sets $(\pi_{-j}, p_{-j})$, firm $j$ solves:

$$\begin{aligned} \max_{\pi_j, p_j} \Pi &= \kappa \int I(WTP_i(p_j) > \pi_j)\Pi_i di + \\ +(1-2\kappa) \int I(WTP_i(p_j) &> \pi_j \ \& \ WTP_i(p_j) - WTP_i(p_{-j}) > \pi_j - \pi_{-j})\Pi_i di. \end{aligned} \tag{7}$$

To solve the duopoly problem, we need to find $(\pi^*, p^*)$ for each $(\pi_{-j}, p_{-j})$; we then look for a symmetric Nash equilibrium in which $\pi^* = \pi_{-j}$ and $p^* = p_{-j}$.

In the duopoly case, we have the extra parameter $\kappa$ that indexes the degree of competition between the two insurers. The monopoly case is a special case when $\kappa = 0.5$, while $\kappa = 0$ results in perfect competition with total surplus equal to the social planner's case. In all intermediate values of the competition parameter, we find a large multiplicity of equilibria; the monopoly solution is almost always an equilibrium, and therefore in Appendix Table A3 we report, in each case, the most competitive equilibrium, which generates the lowest profits. Consider an intermediate case with $\kappa = 0.4$; we get patterns that are very similar to the monopolist case. The insurers set lower cost-sharing and higher premiums for more risk averse consumers, and total surplus increases when individuals are more risk averse. Turning to our key comparison, the simulation of the model predicts that for all combinations of parameter values on consumer risk aversion and competition, increasing the moral hazard parameter $K$ leads to lower cost-sharing for the drug. Hence, profit-maximizing incentives in this set-up of the model lead to an inverse gradient between moral hazard and risk protection that is also present in the social planner's solution.

# B Data construction: classifying drugs to drug types and therapeutic classes

The claim data contain NDC11 codes, which are National Drug Codes assigned to each pharmaceutical substance by the US Food and Drug Administration. NDC11 codes identify

very fine differences across drugs, including strength, dosage, package size, labeler, and pharmaceutical producer.

We define a "drug" by its chemical compound (what the FDA refers to as "non-proprietary names") and whether it is branded or generic. We use publicly available data from the FDA (NDC Database File and Drugs@FDA Database, available at www.fda.gov/Drugs/InformationOnDrugs), to determine the main chemical that a given NDC11 code corresponds to ("non-proprietary name"), and whether a given NDC11 code stands for a branded or a generic medication. The "non-proprietary names" with a branded or generic indicator is what we refer to as a unique "drug" throughout the paper.

To define therapeutic classes, we link the NDC11 codes to the therapeutic class information from the American Hospital Formulary Service's (AHFS) pharmacologic-therapeutic classification of the American Society of Health-System Pharmacists. We use AHFS 8-level classification that consists of a total of 256 therapeutic classes.

We also use create several groupings of drugs and therapeutic classes. Following Einav, finkelstein, and Schrimpf (2015), we define chronic vs. acute drugs empirically. Specifically, a drug is classified as "chronic" if we classify more than 50% of NDC11 codes associated with that drug as "chronic." In turn, an NDC11 code is classified as "chronic" if conditional on filling a claim for a particular NDC11 code, the median beneficiary in our data fills more than two claims for the same NDC11 code within the year in our data; otherwise the NDC11 is classified as acute. Whenever there is substantial variation in the specific NDC11 code used for essentially the same substance and strength, this classification procedure can be noisy, as it may classify some drugs to be "acute" merely because they have many NDC11 codes associated with them. To address this concern, we also use another way to measure drugs prescribed for chronic conditions. We classify drugs (at the NDC11 level) as "maintenance" vs. "non-maintenance" using the classification of First Databank, a drug classification company. This classification relies on the underlying substance in each NDC11, so that when we average the "maintenance" status across NDC11 codes within one "drug," we get almost

perfect split of drugs into the "maintenance" vs. "non-maintenance" category, as all NDC11 codes associated with a specific drug tend to have the same "maintenance" status.

We also classify therapeutic classes as being "maintenance" versus not based on the "maintenance" status of each drug (at the NDC11 code level) within a therapeutic class. Specifically, we compute the fraction of drugs within each therapeutic class that are "maintenance" and assign therapeutic classes to be "maintenance" if more than half of the drugs (at the NDC11 level) in the class are classified as maintenance. The 50 percent cutoff is not consequential in practice; since therapeutic classes roughly capture drugs that are used to treat the same or related conditions, the "maintenance" classification translates cleanly to therapeutic classes - in most cases all NDC11 codes within a therapeutic class are either "maintenance" or not. Since the definition of being a chronic drug is empirical and is based less on conditions and more on the frequency of claiming, this classification does not apply to therapeutic classes; whether drugs are classified as chronic or not tends to vary within a therapeutic class.

# C Alternative elasticity estimates

## C.1 Accounting for delayed purchases

As we highlight in Section II.B, one concern about our elasticity estimates is that individuals that hit the gap in coverage in December may postpone their purchases to January - when their insurance contract re-starts - and appear more elastic. In this Section, we estimate a set of drug- and class-level elasticities adjusted for such potential inter-temporal substitution. To adjust the baseline elasticities, we follow an approach similar in spirit to that implemented in Einav, Finkelstein, and Schrimpf (2015). The idea of the adjustment is to use January claims in the subsequent year to learn about the extent of delayed purchases from the current year, and then "add back" to the baseline elasticity estimate the part of behavioral response that is likely to be due to the inter-temporal substitution to the next year rather than an

inherent price response.

We proceed in several steps. In the first step, we identify a sub-sample of individuals in our baseline sample that we can observe in two consecutive years. Let us call this the "Inter-temporal Substitution (I/S) sample." Before making any adjustments, we verify that our baseline elasticity estimates on the I/S sample are practically identical to the baseline elasticity estimates on the full sample. The correlation between the two sets of elasticity estimates is 0.95 (for drugs) and 0.99 (for classes) if unweighted and 0.99 for drugs and classes if weighted by the number of claims in each drugs or class in the full sample. In the second step, we plot the propensity of claiming a drug or a common therapeutic class in January of year t+1 as a function of the individual's total (relative to the gap) spending in year t. In other words, we re-draw the graphs in Figure 3, keeping the same x-axis and changing the y-axis to be the probability of claiming in January of t+1 instead of the probability of claiming in December of year t. We report these graphs for three most common drugs and therapeutic classes in the top panels of Figures A3 and A4 respectively. The presence of behavior consistent with inter-temporal substitution to the next year is immediately apparent from these figures, as individuals with spending around the gap in year t, increase their purchase probability in year t+1. In order to measure the magnitude of this inter-temporal substitution effect, we proceed to produce the same kind of graphs for a "normal" month that we construct by averaging months March to June; these are illustrated in the bottom panels of Figures A3 (for drugs) and A4 (for classes). We next measure the average propensity of making a claim in March to June of t+1 relative to total spending in year t. Within each bin of year t spending (using $20 bins), we calculate the ratio of the probability of purchasing in January of year t+1 to the probability of purchasing in a "normal" t+1 month. This approach quantifies the extent of inter-temporal substitution or the extent of "excess" purchasing in January. The resulting ratios are illustrated in Figure A5 for the top 3 drugs (top panel) and top 3 therapeutic classes (bottom panel). Consistent with the pent up demand pattern in January graphs, we note that the purchase probability

ratios are close to 1 for individuals that didn't reach the gap in year t, while are 10-15% above 1 for individuals that did reach the gap.

In the last step, we use these relative purchase probabilities to adjust the purchase probability in December of year t in our baseline analysis. We multiply the observed propensity of claiming in December of year t in each spending bin by the ratio of January to "normal" month spending in each spending bin; we do the multiplication at the bin-by-bin level. Visually, this procedure lifts up the post-gap portion of the December claim probability graphs. Figures A6 and A7 compare the baseline December claim probability graphs (top panel) to the inter-temporal substitution- adjusted version (bottom panel) for three most common drugs and therapeutic classes respectively. We can immediately see that adjustment mutes the magnitude of the behavioral response.

With these adjusted December probabilities in hand, we use the exact same empirical approach as discussed in Section II.B to estimate the intertemporal-substitution adjusted elasticities. Figure A8 plots the relationship between the baseline elasticities estimated on the I/S sample (x-axis) and intertemporal-substitution-adjusted elasticities (y-axis). The top panel illustrates this relationship for the set of "common" drugs, and the bottom panel - for the set of "common" therapeutic classes. The adjusted elasticities are lower in magnitude (as expected), but are strongly correlated with baseline elasticities. The unweighted correlation is 0.7 for drugs and 0.9 for classes; a correlation weighted by the number of claims for each drug or therapeutic class is 0.9 for both drugs and classes. Overall, it appears that while inter-temporal substitution to the next year may be making drugs appear overall more elastic, it is not substantially affecting which drugs have higher and which have lower behavioral responses.

We test the robustness of our main empirical results to intertemporal-substitution-adjustment. Tables A4 and A5 replicate our baseline results on the correlation between drugs or therapeutic class elasticities and co-insurance rates, using intertemporal-substitution-adjusted elasticities. We provide three sets of results. Panel A replicates the results from Table 6 in

the main manuscript. Panel B repeats the same analysis, using baseline elasticity estimates computed on the I/S sample. Finally, Panel C reports the point estimates of regressions that use intertemporal-substitution-adjusted elasticities. The results across the three panels are very similar for both drugs and classes, with the magnitude of the coefficients somewhat smaller in the intertemporal-substitution-adjusted case for drugs, and somewhat larger for therapeutic classes. Hence, it appears that drugs that exhibit a stronger behavioral response without accounting for inter-temporal substitution, also exhibit a stronger behavioral response when we take this intertemporal-substitution into account. Thus the finding that private plans set higher co-insurance for more elastic drugs is robust to accounting for inter-temporal substitution.

## C.2 Accounting for potential stockpiling

In Appendix C.1 we considered the possibility that beneficiaries who reach the gap may be reducing their consumption in December in the anticipation of reduced cost-sharing in January. A related concern is the possibility of stockpiling. Beneficiaries who are confident that they won't reach the gap in coverage in December may increase their purchases in December before the contract restarts and they face a deductible in January. To assess whether this possibility could be affecting our results, we re-estimate our baseline elasticities for "common" drugs and classes on a sub-sample of individuals that were enrolled in plans that had no deductibles in the following year. Zero deductible plans are very common in Part D; around 70% of individual-year observations in our sample are enrolled in such plans. On average, individuals that do not reach the gap in a base year and face no deductibles in the following year, should have no differential incentive to stockpile medication in December of the base year, as their cost-sharing effectively doesn't change in January of the following year. At the same time, these individuals may have stronger inter-temporal substitution response when they do reach the gap, so we may expect the elasticities in this "low stockpiling incentive" sample to be somewhat higher than in the overall sample.

Using the same approach as in the baseline analysis, we re-estimate the change in the probability of December claiming for all "common" drugs and therapeutic classes on this sub-sample of "low stockpiling incentive" individuals who are in plans without a deductible. We also re-calculate the average change in the out of pocket prices, allowing for the possibility that plans with no deductibles have different average increase in out of pocket prices as the gap. Figure A9 illustrates the correlation between our baseline elasticity estimates and estimates on the no-deductible "low stockpiling incentive" sub-sample for drugs (top panel) and classes (bottom panel). As expected, the magnitudes for the "low stockpiling incentive" elasticities are slightly higher, especially for the therapeutic classes. The elasticity estimates are correlated (correlation of 0.45 unweighted and 0.69 weighted for drugs; correlation of 0.96 unweighted and 0.97 weighted for classes), suggesting that stockpiling is not driving our main results of the ordinal ranking of drugs across cost-sharing tiers. We test this formally by replicating our baseline specifications that measure the correlation between co-insurance rates and the elasticities. As Table A6 illustrates, the point estimates are slightly attenuated relative to the baseline (for classes) and are noisy for drugs except for the "high frequency sample," but exhibit similarly robust negative slope.[2] Overall, this evidence is reassuring that our results are not driven by stockpiling behavior.

## C.3 Sensitivity to the definition of the end-of-year threshold

For our baseline analysis, we highlighted several reasons for using December as a reasonable cutoff for calculating "spot" or end-of-year demand responsiveness. However, December is of course an arbitrary threshold. In this appendix, we repeat our baseline elasticity estimation for "common" drugs and therapeutic classes using two alternative cutoff specifications: full months of November and December, as well as the narrow window of December 15 to

[2]The relatively low unweighted correlation between baseline and adjusted elasticities for drugs and noisy regression results in Panel A of Table A6 are driven by one outlier drug, for which the elasticity estimate is very high and noisy. In the "low stockpiling incentive" subsample we estimate the elasticity for Digoxin (branded) to be 6.86, while in the baseline sample the elasticity is -2.18. This large elasticity is driven by the denominator that is close to zero in this subsample of individuals and reflects a very small change in price from the pre- to post-gap for this drug.

December 31. We expect the point estimates to be attenuated when we expand the time window, as the response is less pronounced the farther away we move from the end of year, and the estimates to be slightly higher in magnitude when we move closer to the end of year. In both cases, we would not expect to see substantial ordinal changes in which drugs are more and which are less elastic.

Figures A10 and A11 document visually - for three top drugs and therapeutic classes respectively - how the probabilities of purchase change at the two end-of-year definitions. While there are some differences in the magnitudes relative to the baseline, with the response less pronounced at the broader time window, the patterns look broadly similar to those we observed in the baseline Figure 3. We next use the same methods as in the baseline to compute elasticities. As Figures A12 (for drugs) and A13 (for classes) illustrate, both sets of elasticity estimates are highly correlated with the baseline. As expected, the estimates based on November - December are slightly lower in absolute value, while those from the last two weeks of the year are slightly higher. In Tables A8 (for drugs) and A7 (for classes) we repeat our main analysis of the relationship between elasticity levels and cost-sharing. We find that drugs and therapeutic classes for which we estimate more elastic demand have on average higher cost-sharing in private plans. The results are very similar to the baseline not only in sign, but also in magnitude. We conclude, that the relative elasticity across products does not rely specifically on our usage of December as the baseline definition of the "end of year" period.

## C.4 Alternative measure of drug quantity: days supply

In our baseline results, we have focused on estimating an extensive margin elasticity by capturing how the probability of filling a prescription for a drug or therapeutic class changes with the change in prices. This does not capture the potential intensive margin response - some consumers may still fill the prescription when prices go up, but reduce the quantity of the fill. Both measures of demand response are valuable and reveal different potential

responses by consumers. We hypothesize that drugs and therapeutic classes for which we find a stronger extensive margin response are also likely to have a stronger intensive margin response. In this appendix we empirically test this hypothesis. We estimate the total quantity margin response using "days supply" as a measure of fill quantity for "common" drugs and therapeutic classes and correlate these "quantity" elasticities with our baseline elasticity estimates.

We proceed with the same steps as in Section II.B with some modifications to account for the days supply measure of response. With this new response measure, our empirical strategy is to compare the average days supply purchased of a specific product between individuals whose total annual spending is "just below" and individuals whose total spending is "just above" the kink location. The days supply measure commonly reflects the number of days for which the individual will be able to take the prescribed medication dosage. This is a convenient measure of quantity, as it allows us to meaningfully compare purchases across different individuals and different drugs (or classes) without the need to adjust for inherent differences in physical units and prescribed strengths across individuals and chemical substances. Days supply is mostly commonly equal to 30, 60, or 90 days for 1 to 3 months of medication.With this new quantity metric, our measure of demand is the average number of days supply for a particular drug or therapeutic class in the last month of the year (December).

To account for the quantity measure of demand response, we modify the elasticity formula slightly. For each product $d$, we define the product-specific elasticity of demand by:

$$\sigma_d = \frac{\%\triangle Q_d(Dec)}{\%\triangle OOP_d} = \frac{(Q_d^{obs}(Dec) - Q_d^{pred}(Dec))/Q_d^{pred}(Dec)}{(OOP_d^{gap} - OOP_d^{pregap})/OOP_d^{pregap}}. \tag{8}$$

The changes are associated with the event of entering the donut hole. The denominator of the elasticity is the same as in the baseline - the percentage change in the average (per claim) out-of-pocket cost of a given drug (class) that occurs at the kink. $OOP_d^{gap}$ measures

the average out-of-pocket payment (in absolute $) for a given drug (class) in the donut hole (which comes quite close to the total cost of the drug in the vast majority of plans), and $OOP_d^{pregrap}$ measures the average out-of-pocket payment for that product between the deductible and the kink.

The numerator of the elasticity is different and now corresponds to the percentage change in the average (within a total spending bin) days supply of a December purchase for a given product. We define this as the difference between the actual average (within a total spending bin) days supply of a December purchase, $Q_d^{obs}(Dec)$, and the predicted number of days supply of a December purchase, $Q_d^{pred}(Dec)$ in the (counterfactual) absence of the donut hole. Both actual and predicted days supply are measured for individuals whose annual spending is just above the kink; specifically, we focus on individuals who entered the donut hole, but whose annual spending is no more than $400 higher than the kink location. We then define the actual days supply of a December purchase as the average number of day supply purchased by these individuals of a given drug or in a given therapeutic class in December.

To construct the counterfactual (in the absence of the kink) December day supply measure $Q_d^{pred}(Dec)$ for individuals whose annual spending is between $0 and $400 above the kink, we estimate the statistical relationship between average days supply and annual spending for individuals whose annual spending is below the kink. Unlike with the probability measure in the baseline specification, there are a number of natural statistical relationships to fit. We estimate two different versions of this relationship, using linear and exponential specifications. In the linear case, we fit the following statistical relationship for each product:

$$Q_{db} = \alpha_d - \gamma_d e_b + \epsilon_{db}, \tag{9}$$

where the unit of observation is a total annual spending bin $b$, $Q_{db}$ is the average day supply in that bin for drug or therapeutic class $d$ in December, and $e_b$ is the lower bound of the

spending bin $b$ (we use spending bins of \$20 each). To allow for a different growth rate at higher overall spending levels, we also fit an exponential relationship of the form:

$$exp(Q_{db}) = \alpha_d - \gamma_d e_b + \epsilon_{db}, \tag{10}$$

We fit both of these regressions using only observations from individuals with total expenditures that are sufficiently below the kink location (we use all spending bins that are between \$2,000 and \$500 below the kink), assuming that late in the year individuals who are \$500 or more below the kink are sufficiently certain to not hit the kink by the end of the year. We use the estimates from equations (9) and (10) to project them (out of sample) for spending bins that are above the kink, thus constructing the predicted December days supply measure $Q_d^{pred}(Dec)$ for individuals with total spending of zero to \$400 above the kink. The top panels of Figures A14 and A15 illustrate this approach for top 3 drugs and therapeutic classes, respectively. The long-dashed line illustrates the linear regression fit and the short-dashed line illustrates the exponential fit, both recording the in and out of sample predictions of the average days supply in December as a function of total spending. To illustrate the part of the quantity response that stems only from the decrease in the days supply conditional on making any purchase, the bottom panels of Figures A14 (for drugs) and A15 (for classes) plot the conditional response, where we restrict the sample to individuals that made at least one claim for a given drug or therapeutic class in December. We observe a sharp drop in the number of days supply purchased right around the kink for those individuals that are making a purchase, suggesting that the overall days supply response represents a mixture of the extensive and intensive response margins. To capture just the conditional intensive margin response, we calculate the predicted and observed conditional number of days supply around the kink, following the same method (with the linear statistical relationship) as outlined above for the unconditional case.

The comparison of predicted and observed (unconditional and conditional) days supply measures right around the donut hole allows us to quantify the "quantity" demand

response for each of our common therapeutic classes. As in the baseline calculations, we then combine these estimates of the quantity response with the empirically observed change in out-of-pocket price at the donut hole to obtain estimates of "quantity" elasticity in each case. We end up with three sets of "quantity" elasticities: (i) unconditional quantity elasticity using a linear counterfactual prediction; (ii) unconditional quantity elasticity using an exponential counterfactual prediction, and (iii) conditional quantity elasticity using a linear counterfactual prediction. In the next step, we ask how these three measures of "quantity" elasticities relate to our baseline extensive margin elasticities. Figures A16 and A17 illustrate the correlation of all three new elasticity measures with our baseline elasticity estimates for drugs and classes, respectively. All unconditional measures are highly correlated. In both unconditional cases (measure (i) and (ii) above), both unweighted and weighted correlation between the quantity elasticities and baseline elasticities is close to 1. For the conditional case, the unweighted correlation between the quantity and baseline elasticities is 0.1 for drugs and 0.5 for classes, while the weighted correlation that accounts for differences in the number of claims per drug or therapeutic class is 0.8.

Thus, overall we conclude that products for which consumers exhibit stronger extensive margin response in the probability of claiming, are more likely to also have a stronger behavioral response when we take the quantity dimension (here measured in days supply that are purchased) into account. This relationship is also reflected in our main results relating elasticity measures to co-insurance rates. As Tables A9 (for drugs) and A10 (for classes) report, all measures of "quantity elasticities" exhibit the same negative correlation with co-insurance rates as the one we find in our baseline results. For the case when we include the extensive margin response, the point estimates are very similar to the baseline both in sign and magnitude. The strong negative relationship holds also when we take into account only the intensive margin response, conditional on purchasing; in this case the point estimates are substantially higher in absolute value than in the baseline, reflecting the compressed scale of conditional elasticity estimates.

## C.5 Accounting for plan selection

In this appendix we provide a check on our elasticity estimates that attempts to account for the potential concern about plan selection. If individuals sort into plans based on their likelihood of reaching the gap or their expected behavioral response in the gap, then we may expect, for example, individuals with more elastic demand to choose plans that have lower change in out of pocket prices at the gap. To address this concern, we re-do our baseline elasticity estimates (for "common" drugs and therapeutic classes) on a sub-sample of individuals that all were enrolled in plans that had no coverage in the gap. About 85 percent of individuals meet this criterion. On average, these individuals should all expect to see a high increase in the out of pocket prices of their prescriptions, since their plans offer zero coverage in the gap.

Using the same approach as in the baseline analysis, we re-estimate the change in the probability of December claiming for all "common" drugs and therapeutic classes. We also re-calculate the average change in the out of pocket prices. This gives us a set of new elasticity estimates. Figure A18 (top panel for drugs and bottom panel for classes) illustrates that this version of elasticity estimates is highly correlated with our baseline calculations, for unweighted and weighted correlation coefficients of about 0.98 for therapeutic classes, and 0.75 (unweighted) and 0.98 (weighted) for "common" drugs. Table A11 reports our main results that relate co-insurance rates with elasticity estimates. The results are similar to the baseline both in sign (higher co-insurance rates for more elastic products) and magnitude. This evidence is reassuring that selection of plans is unlikely to substantially bias our elasticity estimates, or our main results measuring the relationship between cost-sharing and the degree of moral hazard.

## C.6 Leave-one-out elasticity computation

One potential concern about our baseline specifications in Table 6 that relate elasticity estimate to co-insurance rates is that out of pocket prices that we use in the denominator

of the elasticity formula also enter the process of computing the co-insurance rates. The presence of related objects on the left and the right hand side of our regression could be biasing the point estimates. To test the sensitivity of our results to this issue, we construct a set of what we refer to "leave-one-out" elasticities and re-estimate the specifications in Table 6.

Recall that our baseline estimating equation is

$$p_{dj}^{pregap} = \alpha_j + \beta\sigma_d + \epsilon_{dj},$$

where $p_{dj}^{pregap}$ denotes the pre-gap co-insurance rate for a drug (or class) in plan $j$, $\alpha_j$ denotes the plan fixed effects, and $\sigma_d$ denotes the elasticity of product $d$ estimated in Section II. The coefficient of interest, $\beta$, measures the correlation between pre-gap co-insurance and elasticity. The concern is that the out of pocket price for drug $d$ in plan $j$ – in other words, the numerator of $p_{dj}^{pregap}$– also appears in the denominator of $\sigma_d$, as we use out of pocket price records from all plans when estimating baseline elasticities.

In this specification check, we recompute a set of plan-specific elasticities $\sigma_{-jd}$ that leave out claims coming from plan $j$ when computing the change in out of pocket prices. As prices across plans and time could be correlated we do two versions of this check. First, we leave out only observations for a specific plan (in a specific year) - this leaves out relatively little data, especially for small plans. Second, we do a more conservative version of the leave-one-out exercise, leaving out insurer-level observations for all years. In other words if plan $j$ is a plan offered by insurer $n$ in year $t$, then the denominator of the elasticity associated with this plan $\sigma_{-jd}$ will be computed only using data that does not have any claims from any plans offered by insurer $n$ in any years of the data. For large insurers, this drops a substantial number of observations. For both of these specifications, we then estimate the following relationship:

$$p_{dj}^{pregap} = \alpha_j + \beta\sigma_{-jd} + \epsilon_{dj},$$

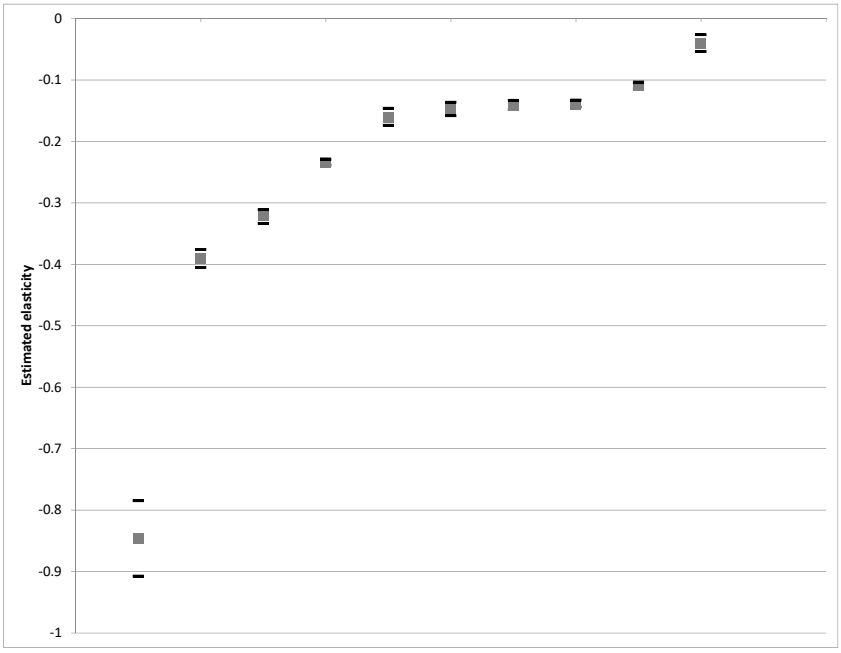
For the case where we only leave out observations for a specific plan (year), the leave-one-out elasticities are practically identical to the baseline estimates. With insurer-level leave-one-out computation, there is a larger difference between the two sets of elasticity estimates, although they are still strongly correlated.

In Tables A12 and A13 we quantify these similarities by replicating our main analysis with these new elasticity estimates. We report two versions of Table 6 that use the leave-one-out elasticity estimates: Table A12 uses plan-level leave-one-out elasticities, while Table A13 uses the insurer-level leave-one-out. As the elasticity estimates with the plan-level exclusion of data are very close to the baseline, there is little difference in the coefficients relative to Table 6. in the main text. In Table A13, the levels of estimated coefficients for the top panel with drug-level analysis fall by roughly a half. The estimates for therapeutic classes are unchanged.[3] Overall, these results suggest that the baseline drug-level estimates could have a bias from using related price measures on the left and the right hand side of the regression equation. The qualitative conclusions, however, remain the same as in the baseline analyses.

[3]The point estimates for therapeutic classes are higher than in the baseline specification in Table 6. This stems from the fact that in order to compute the leave-one-out price changes at the therapeutic class level we have to use slightly different weighting procedures, depending on the level of data that we leave out. As we discuss in the main text, for therapeutic classes, we weight the post-gap claims for each NDC11 code within a therapeutic class with its pre-gap weights, so as to not conflate our computation of the change in out of pocket prices with NDC11-level substitution within a therapeutic class. When we compute leave-one-out elasticities, we apply the pre-gap weights not only at NDC11 level, but at NDC11-plan (or insurer) level, which is a more precise weighting procedure and is less conservative than our baseline. When we repeat the baseline (without leave one out) using these less conservative weights, we get point estimates for therapeutic classes that are virtually identical to Table A13, indicating that for therapeutic classes $\sigma_d$ is essentially identical to $\sigma_{-jd}$.

Figure A1: Confidence intervals for baseline elasticity estimates

(a) Top ten common therapeutic classes




(b) Top ten common drugs

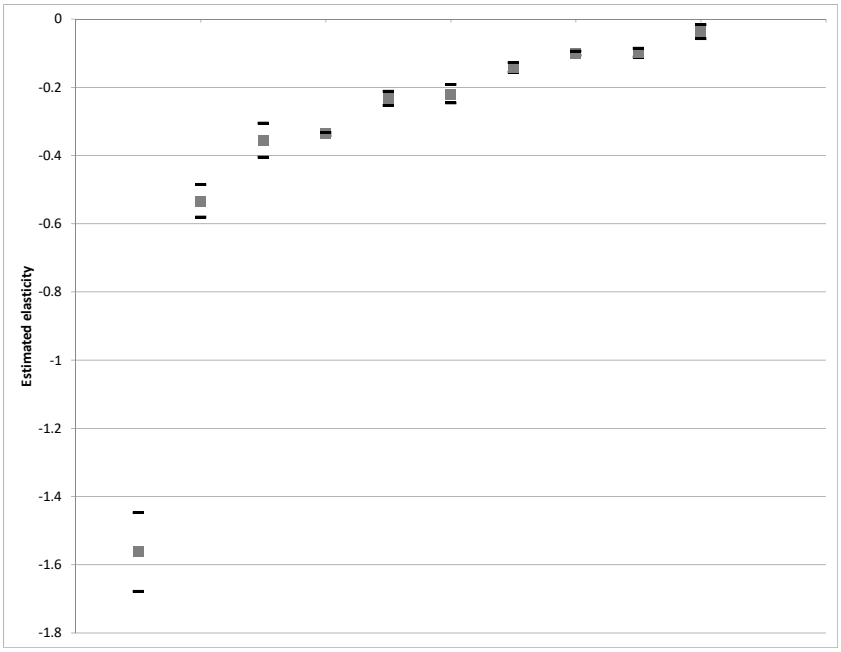
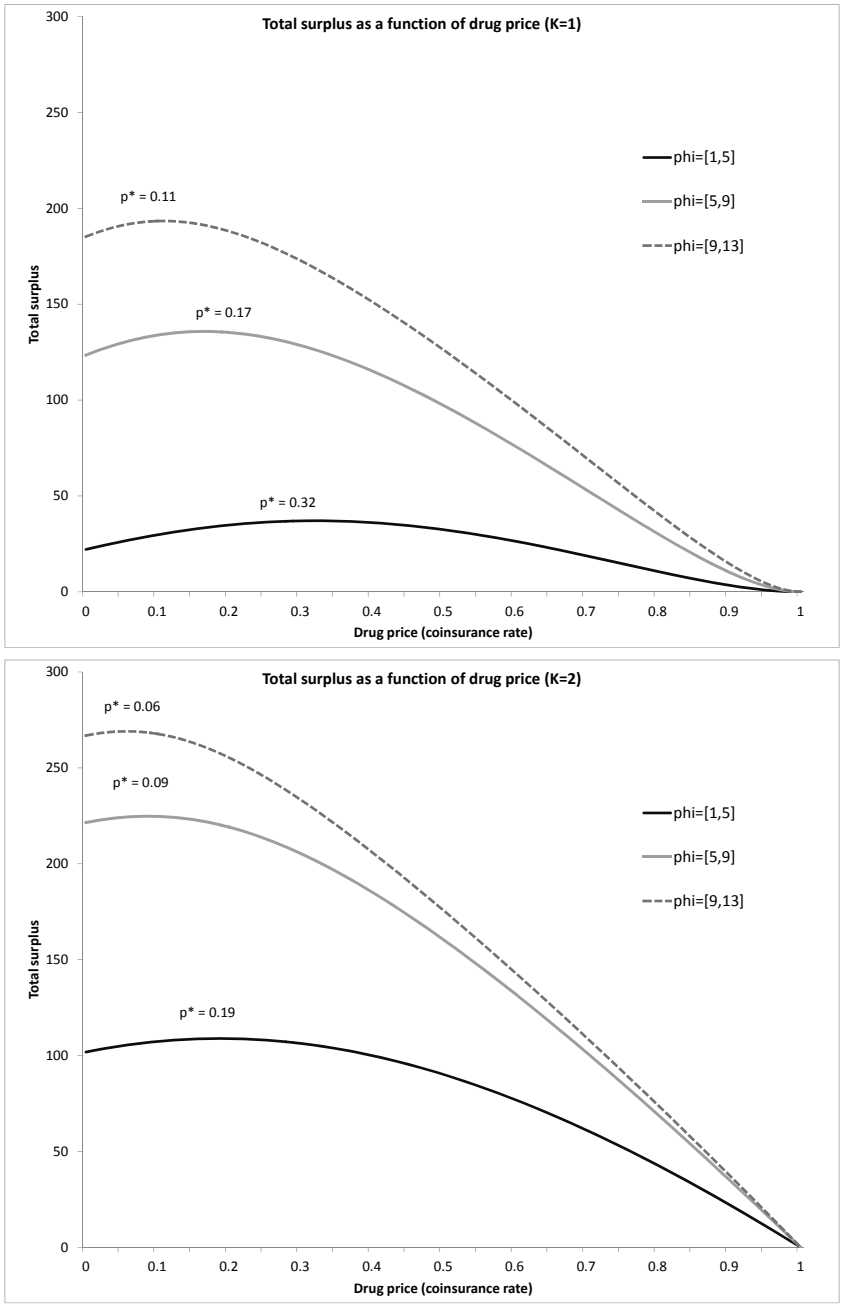



Figure reports point estimates of the elasticities and the associated 95% confidence intervals for the ten most frequently claimed therapeutic classes (top panel) and the ten most frequently claimed drugs (bottom panel). The confidence intervals are based on 100 bootstrap draws as described in Section II.B.

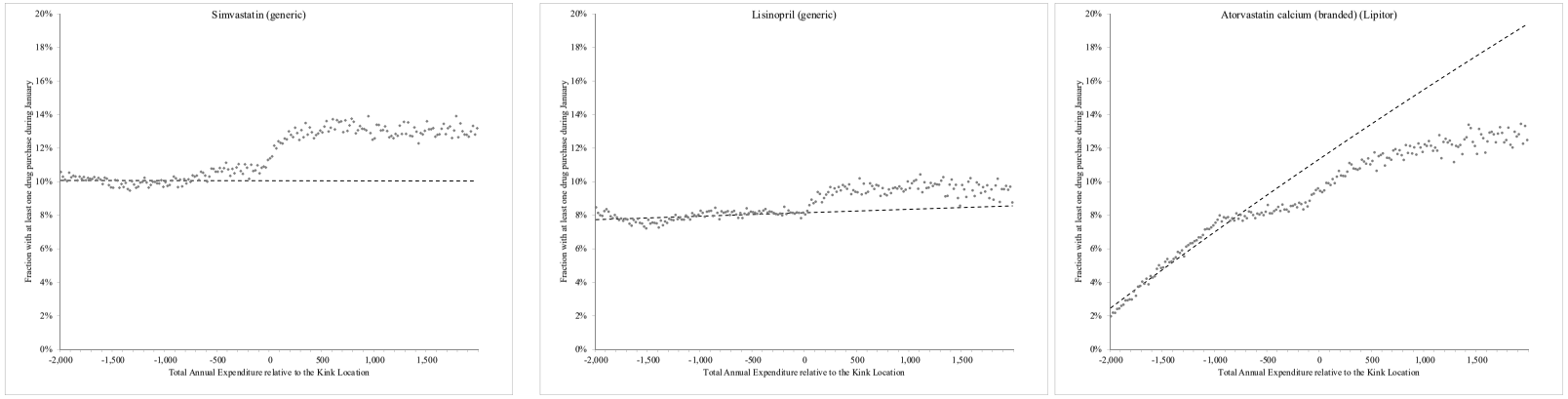
Figure A2: Graphic Representation of the Social Planner's Problem




The graphs plot the willingness to pay for insurance as a function of drug price for the model described in Appendix A. The top panel plots the willingness to pay for the moral hazard parameter $K = 1$, while the bottom panel for $K = 2$. The maxima points mark the social planner's solutions for different distributions of risk aversion.

Figure A3: Drug claim propensity in January and a "normal" month as a function of annual spending in previous year

(a) Top 3 Common Drugs; January




(b) Top 3 Common Drugs; "normal" month

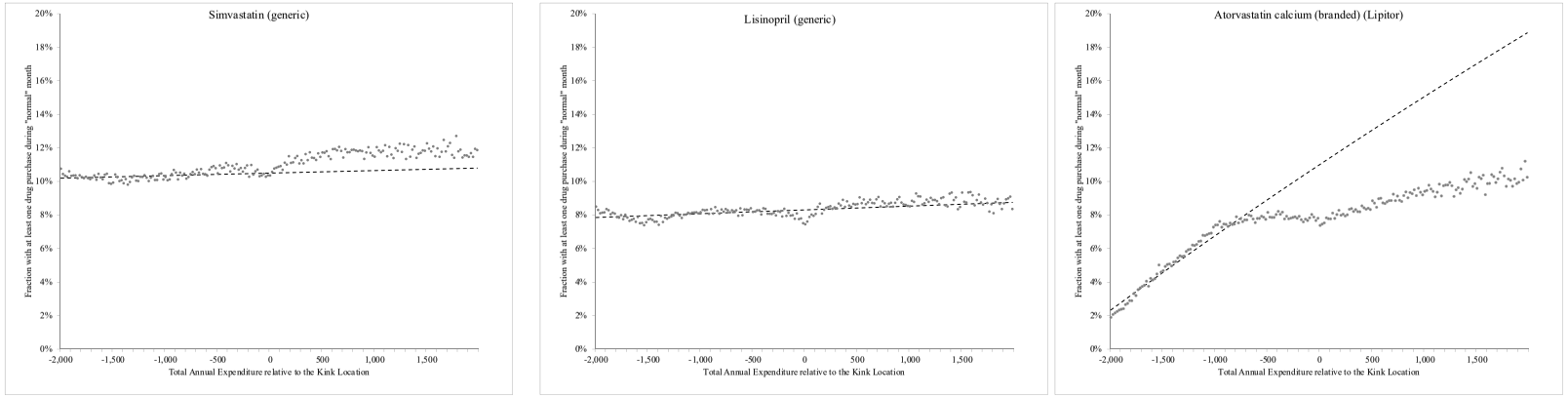
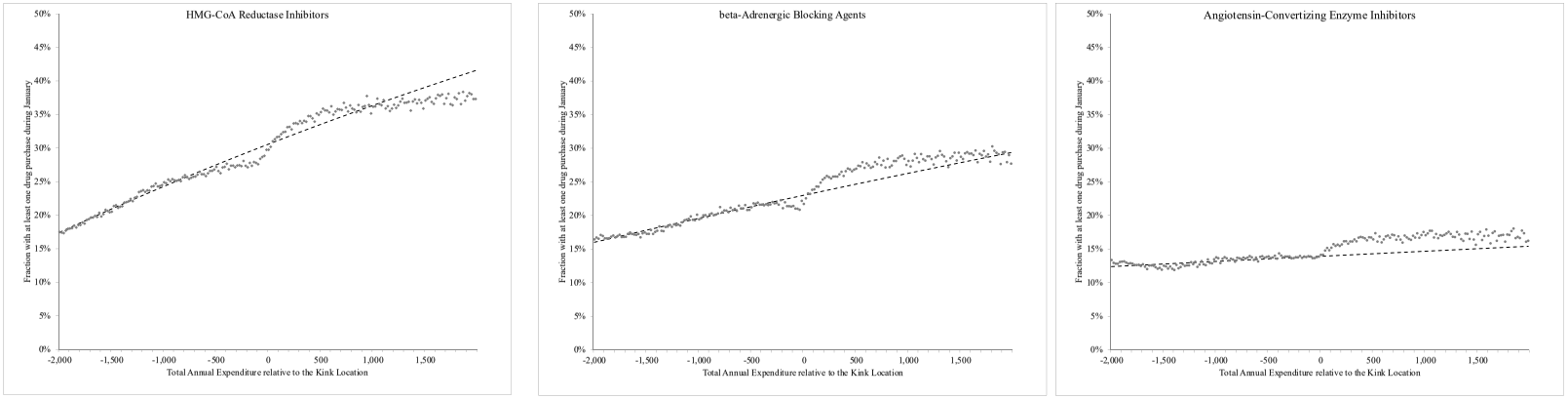



Figure shows the probability of filling a claim in January (top panel) and on average in March to June (bottom panel) for the top three "common" drugs. The horizontal axis is the individuals' total annual drug spending relative to the (year-specific) kink location in year $t$; we bin spending in \$20 bins. The vertical axis is the fraction of individuals within each bin with at least one claim in January or (on average) March-June of the following year $t+1$ associated with the selected drug.

Figure A4: Therapeutic class claim propensity in January and a "normal" month as a function of annual spending in previous year

(a) Top 3 Common Therapeutic Classes; January




(b) Top 3 Common Therapeutic Classes; "normal" month

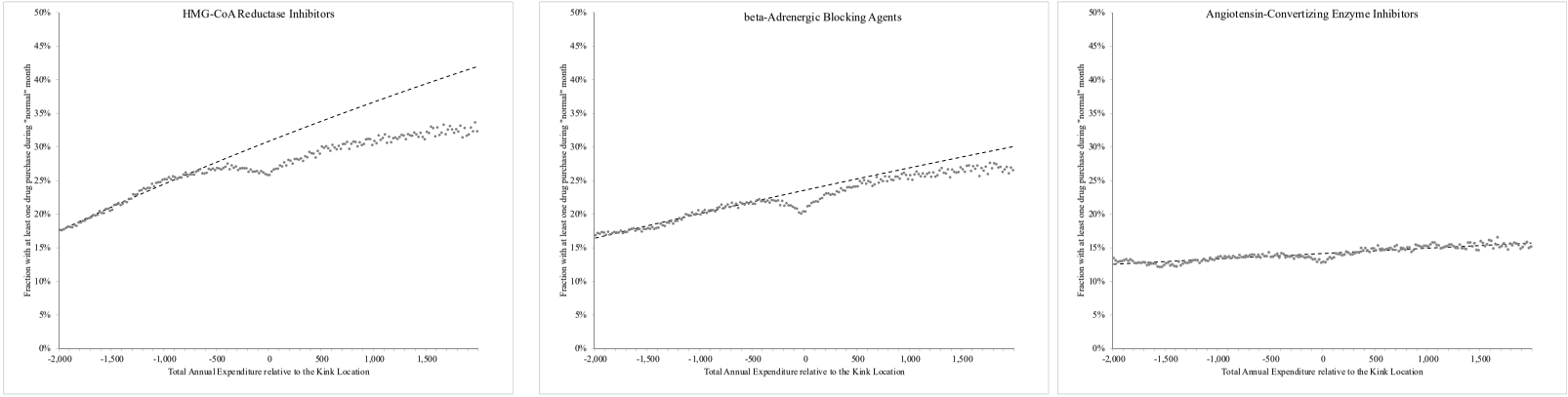
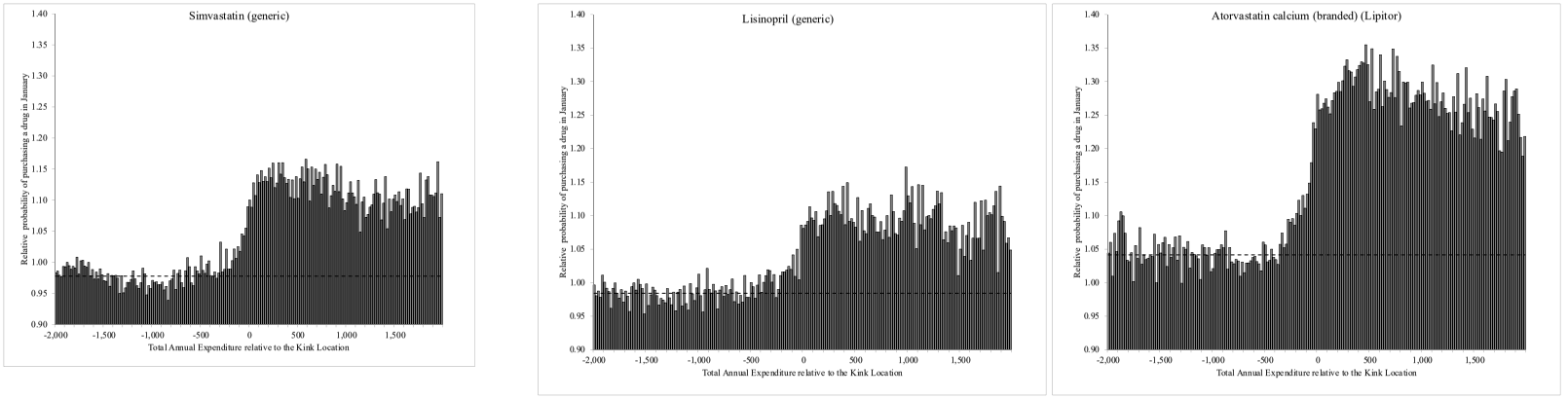



Figure shows the probability of filling a claim in January (top panel) and on average in March to June (bottom panel) for the top three "common" therapeutic classes. The horizontal axis is the individuals' total annual drug spending relative to the (year-specific) kink location in year $t$; we bin spending in \$20 bins. The vertical axis is the fraction of individuals within each bin with at least one claim in January or (on average) March-June of the following year $t+1$ associated with the selected therapeutic class.

Figure A5: Relative claim propensity in January

(a) Top 3 common drugs




(b) Top 3 common therapeutic classes

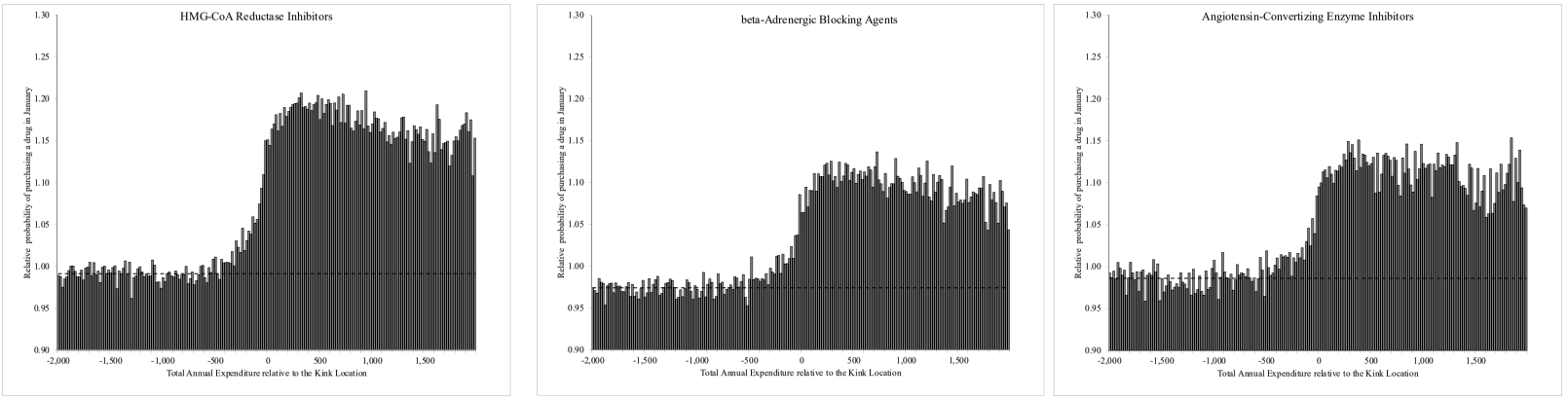
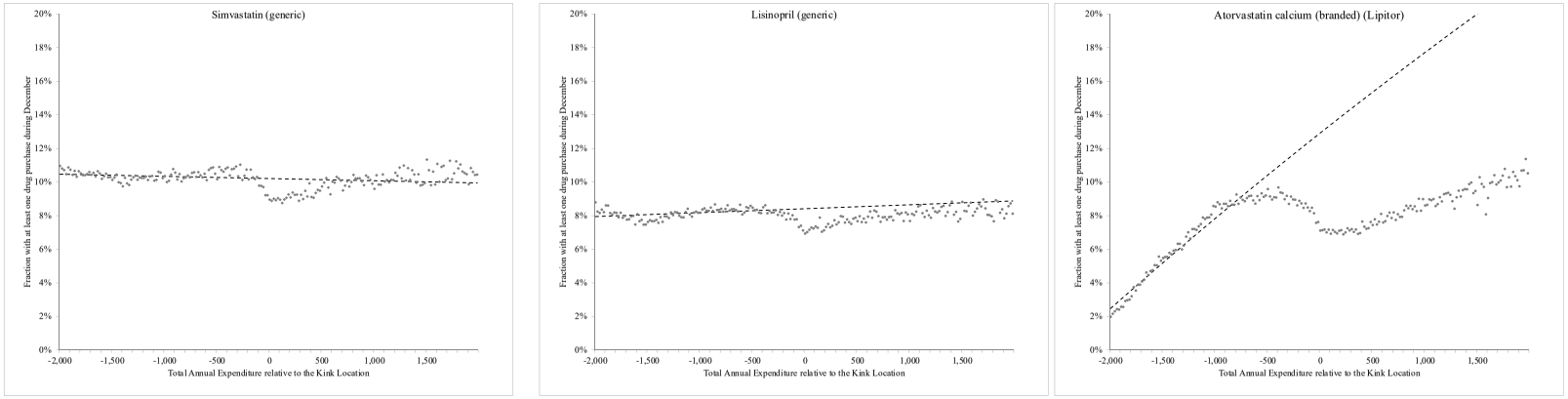



Figure shows the probability of filling a claim in January divided by the average probability of filling a claim in March to June for the top three "common" drugs (top panel) and therapeutic classes (bottom panel). The horizontal axis is the individuals' total annual drug spending relative to the (year-specific) kink location in year $t$; we bin spending in \$20 bins. The vertical axis is the bin-by-bin ratio of the fraction of individuals within each bin with at least one claim in January to the fraction of individuals with at least one claim in March-June (on average); both fractions are measured in the following year $t+1$.

Figure A6: Drug claim propensity in December with and without the inter-temporal substitution adjustment

(a) Without inter-temporal substitution adjustment (baseline)




(b) With inter-temporal substitution adjustment (baseline)

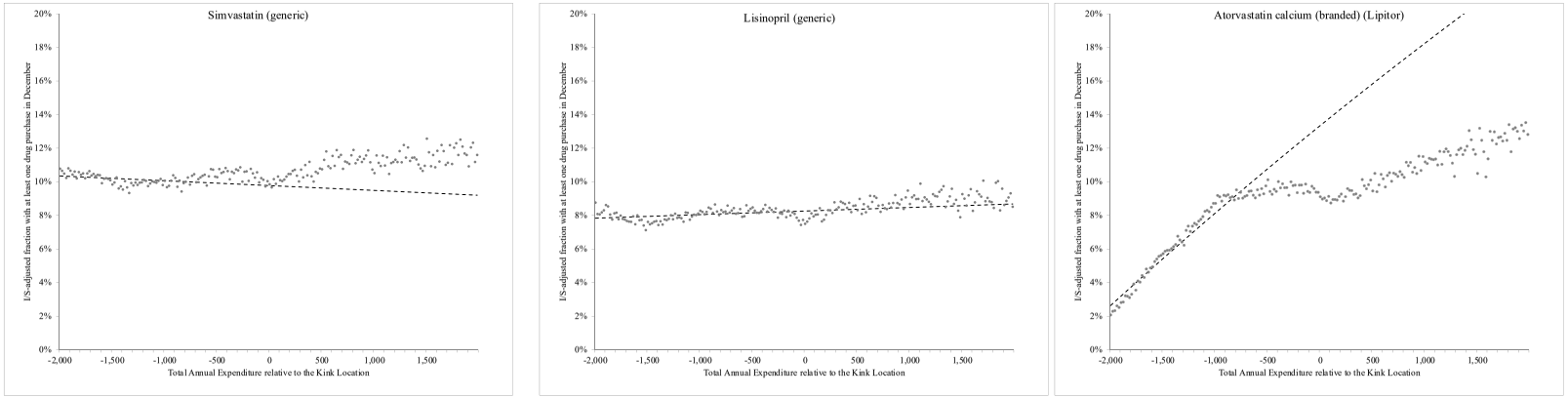
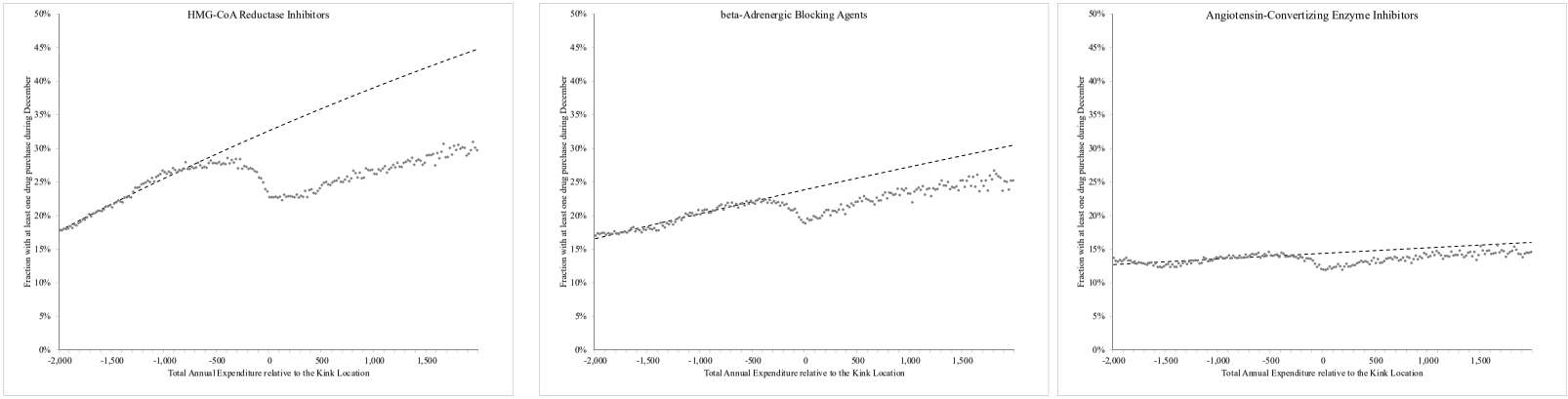



Figure shows the probability of filling a claim in December for the top three "common" drugs. The top panel reports the baseline analysis from the manuscript. The bottom panel repeats the analysis using inter-temporal substitution adjustment of the claim probability. The adjustment is computed by multiplying - bin by bin - the claim probabilities of the top panel with the ratios reported in Figure A5. The horizontal axis is the individuals' total annual drug spending relative to the (year-specific) kink location in year $t$; we bin spending in \$20 bins. The vertical axis is the fraction of individuals within each bin with at least one claim in December of the same year $t$ (as observed in the data in the top panel; and adjusted for intertemporal-substitution in the bottom panel) associated with the selected drug.

Figure A7: Therapeutic class claim propensity in December with and without the inter-temporal substitution adjustment

(a) Without inter-temporal substitution adjustment (baseline)




(b) With inter-temporal substitution adjustment (baseline)

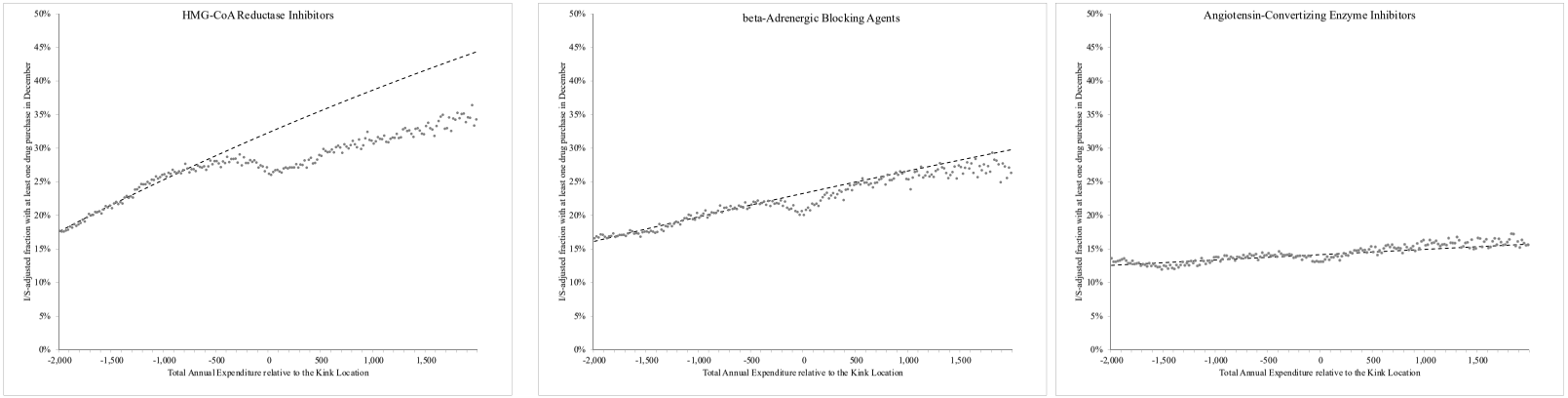



Figure shows the probability of filling a claim in December for the top three "common" therapeutic classes. The top panel reports the baseline analysis from the manuscript. The bottom panel repeats the analysis using inter-temporal substitution adjustment of the claim probability. The adjustment is computed by multiplying - bin by bin - the claim probabilities of the top panel with the ratios reported in Figure A5. The horizontal axis is the individuals' total annual drug spending relative to the (year-specific) kink location in year $t$; we bin spending in \$20 bins. The vertical axis is the fraction of individuals within each bin with at least one claim in December of the same year $t$ (as observed in the data in the top panel; and adjusted for intertemporal-substitution in the bottom panel) associated with the selected therapeutic class.

Figure A8: Baseline and intertemporal-substitution adjusted elasticity estimates

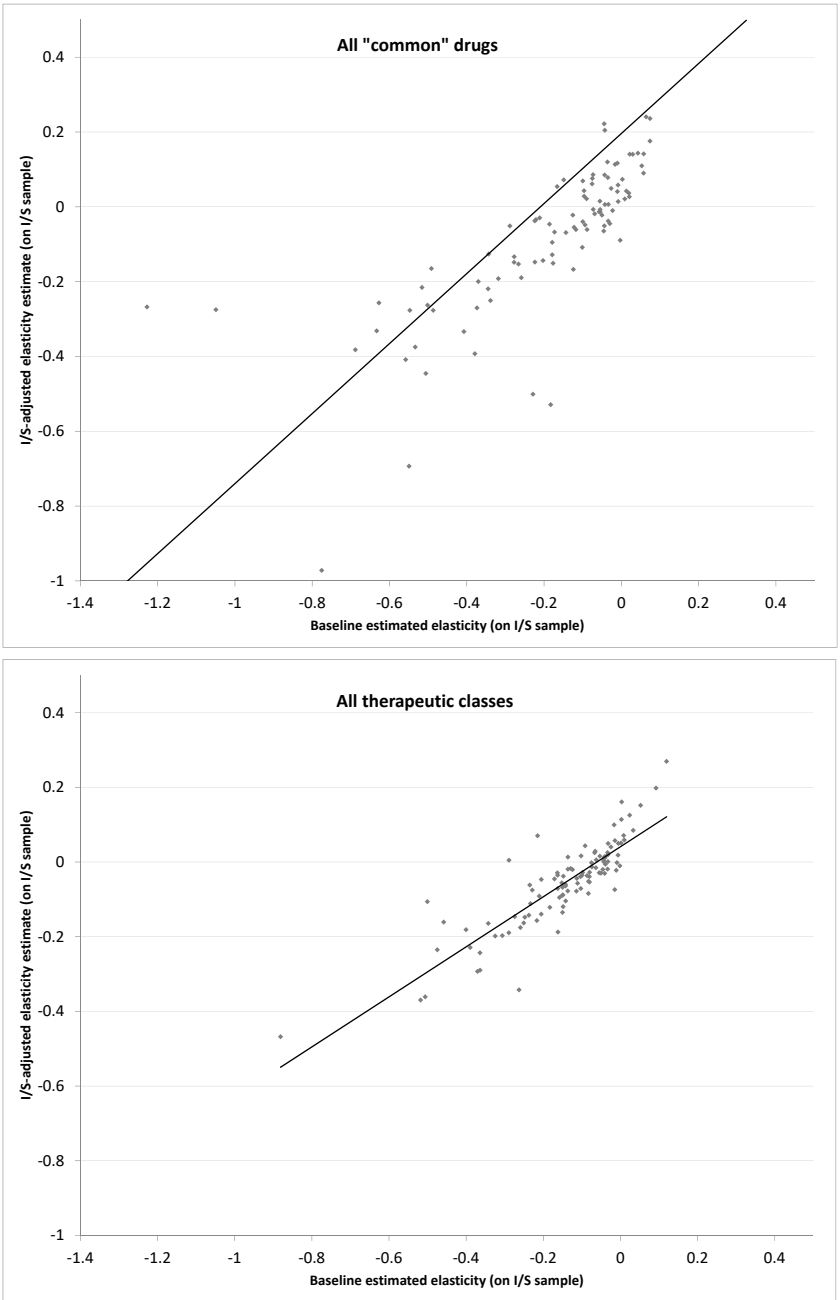



Figure shows the relationship between baseline elasticity estimates for common drugs (top panel) and therapeutic classes (bottom panel) and intertemporal-substitution-adjusted elasticity estimates. On the x-axis we record baseline elasticities estimated on the inter-temporal substitution analytic sample. On the y-axis we record elasticity estimates adjusted for inter-temporal substitution. The solid line marks an unweighted OLS regression relating the two elasticity measures.

Figure A9: Correlation between baseline elasticities and elasticities estimated on a sample of individuals with no deductibles in $t+1$

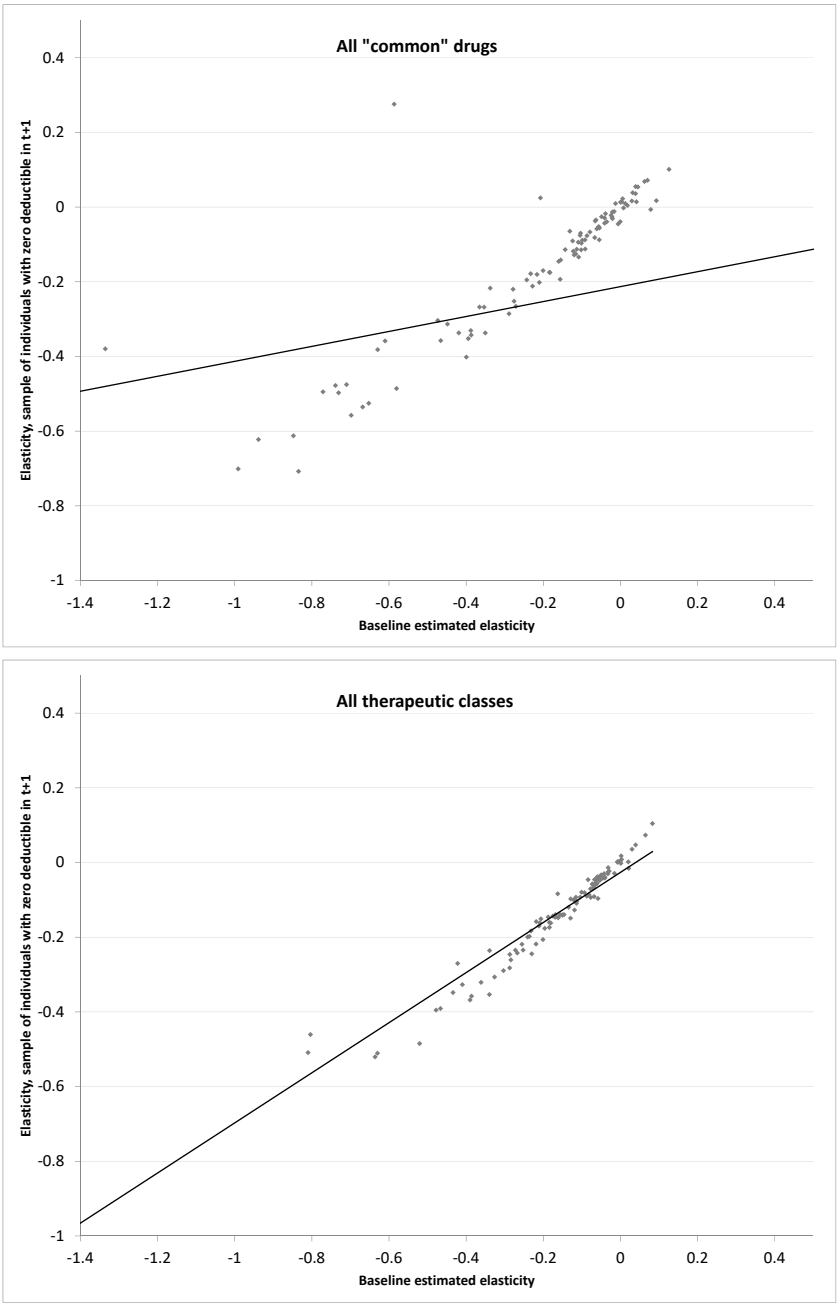
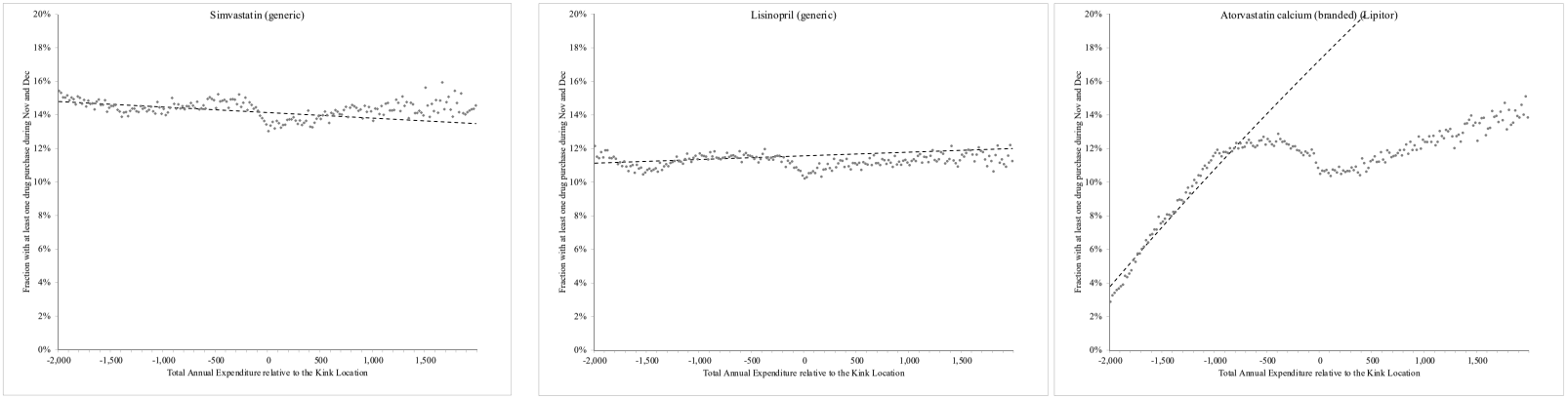



Figure shows the relationship between baseline elasticity estimates (x-axis) for common drugs (top panel) and therapeutic classes (bottom panel) and elasticity estimates done on a sample of individuals that in $t+1$ were enrolled in plans that did not have a deductible (y-axis), where we consider the latter a "low stockpiling incentive" sample. The solid line marks unweighted OLS regressions relating each pair of elasticity measures.

Figure A10: Probability of making a drug claim at the end of the year

(a) End of year defined as November and December




(b) End of year defined as December 15 - December 31

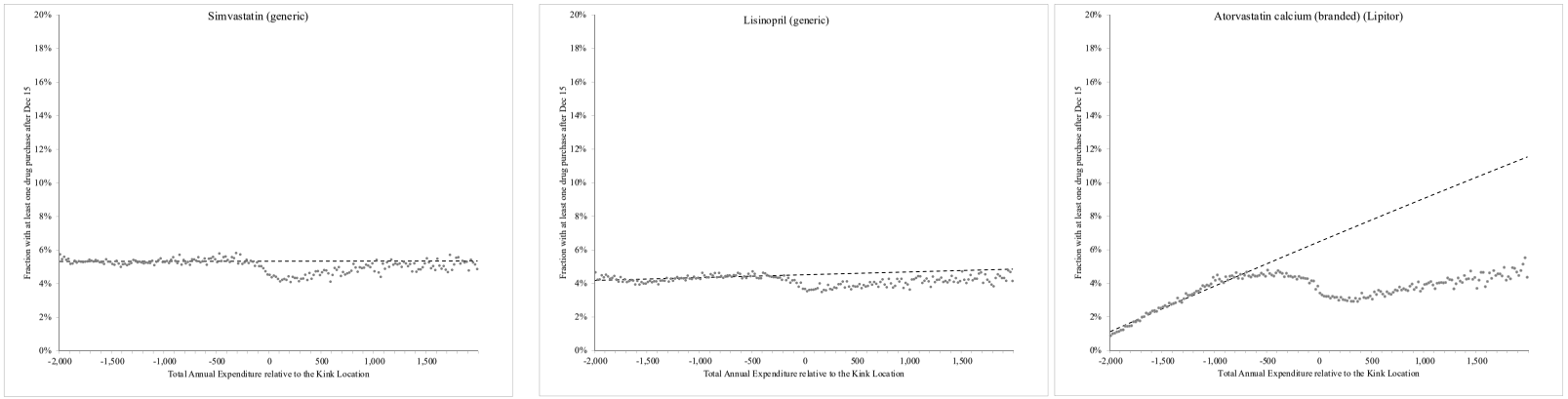
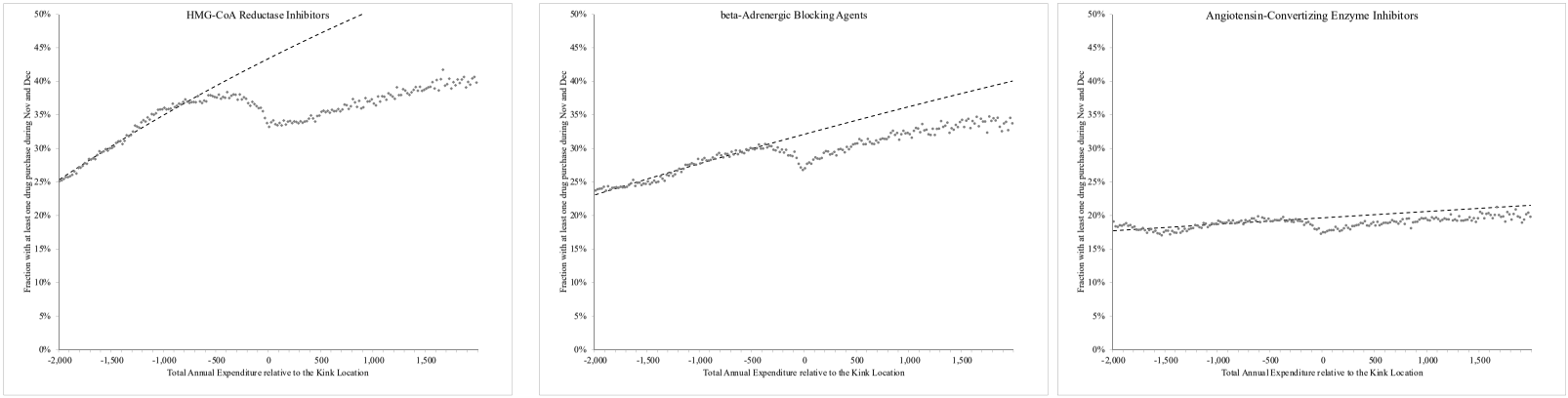



Figure shows the probability of filling a claim at the end of year for the top three "common" drugs. The top panel reports the results where we define the end of year to be claims in the months of November and December. The bottom panel defines end of year as the last two weeks of the year - December 15 to December 31. The horizontal axis is the individuals' total annual drug spending relative to the (year-specific) kink location in year $t$; we bin spending in \$20 bins. The vertical axis is the fraction of individuals within each bin with at least one claim in the respective end of year period of the same year $t$ associated with a given drug.

Figure A11: Probability of making a therapeutic class claim at the end of the year

(a) End of year defined as November and December




(b) End of year defined as December 15 - December 31

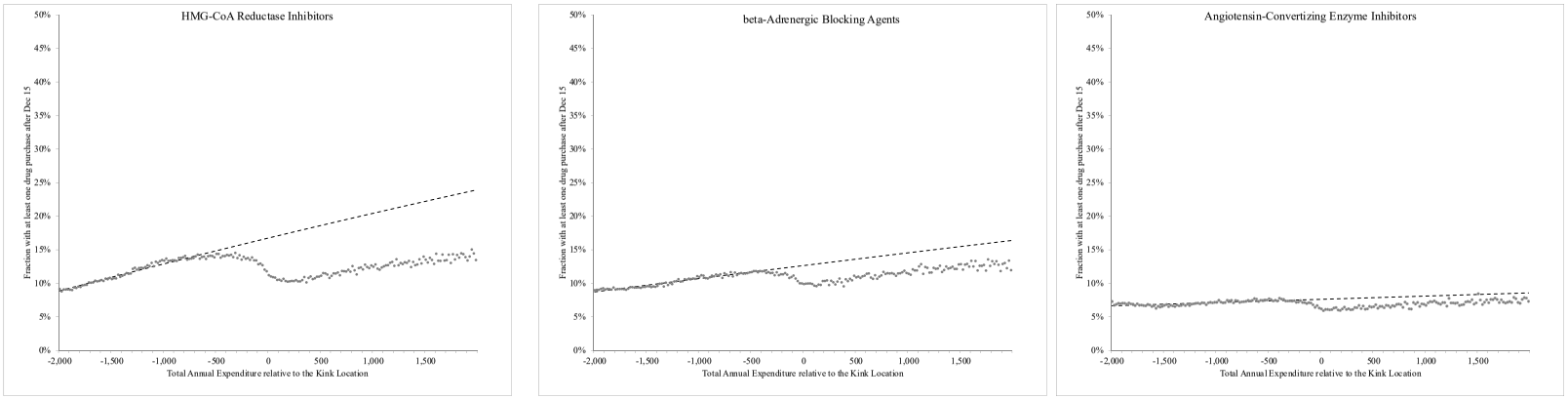
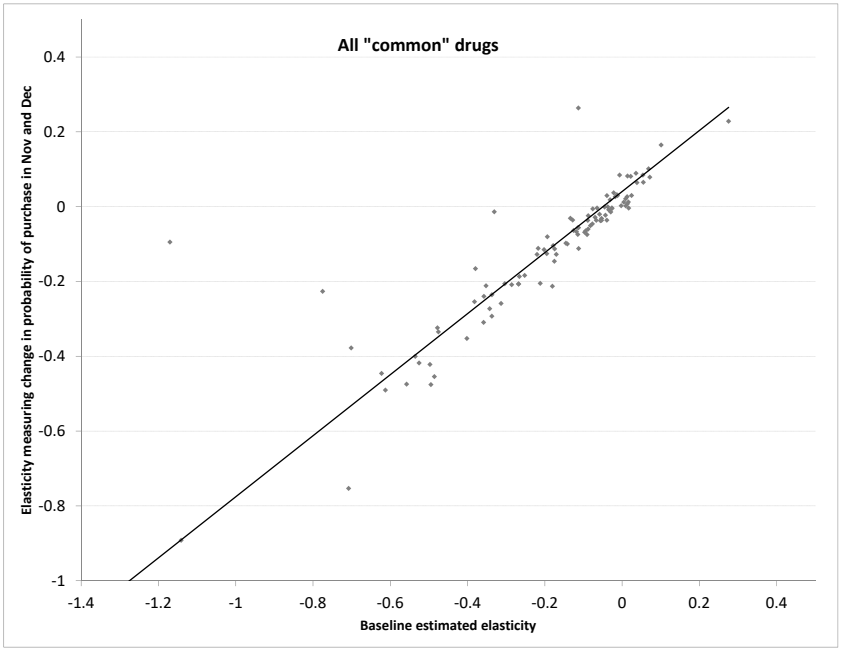



Figure shows the probability of filling a claim at the end of year for the top three "common" therapeutic classes. The top panel reports the results where we define the end of year to be claims in the months of November and December. The bottom panel defines end of year as the last two weeks of the year - December 15 to December 31. The horizontal axis is the individuals' total annual drug spending relative to the (year-specific) kink location in year $t$; we bin spending in \$20 bins. The vertical axis is the fraction of individuals within each bin with at least one claim in the respective end of year period of the same year $t$ associated with a given therapeutic class.

Figure A12: Drug elasticity estimates with alternative end of year cutoff definitions

(a) November and December




(b) December 15th-December 31st

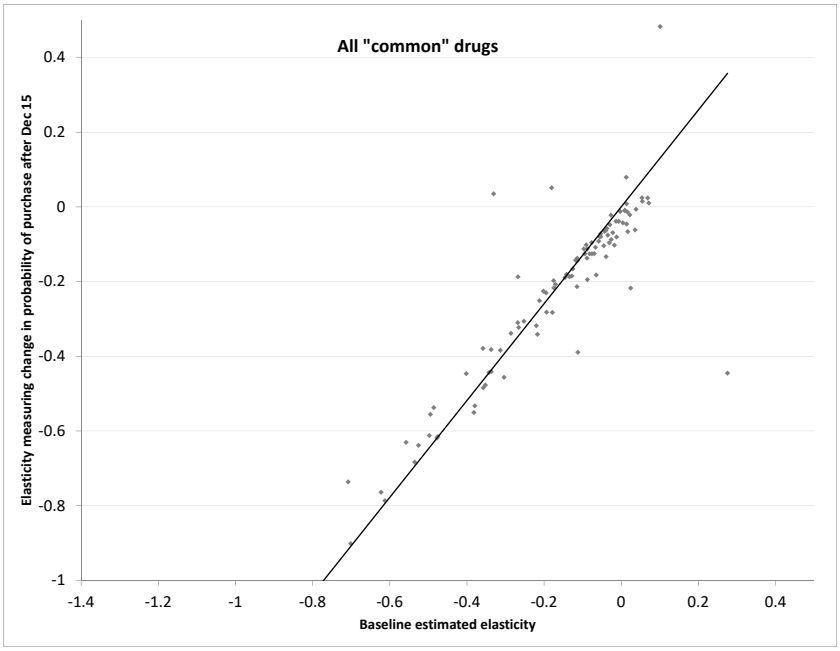
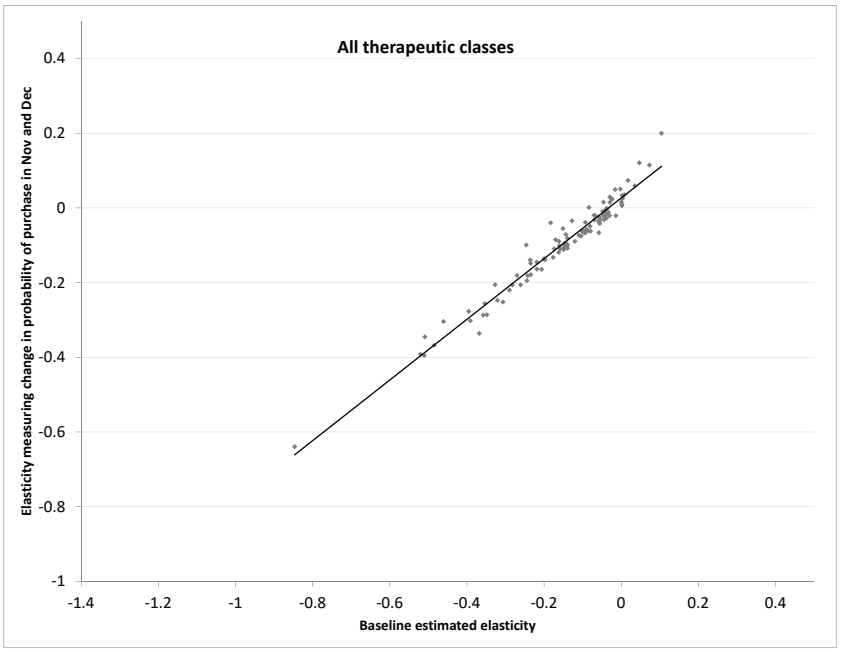



Figure shows the relationship between baseline elasticity estimates for common drugs and elasticity estimates that use alternative definitions of the end of year cutoffs (November and December in the top panel and the last two weeks of December in the bottom panel). The solid line mark unweighted OLS regressions relating the two elasticity measures.

Figure A13: Therapeutic class elasticity estimates with alternative end of year cutoff definitions

(a) November and December




(b) December 15th-December 31st

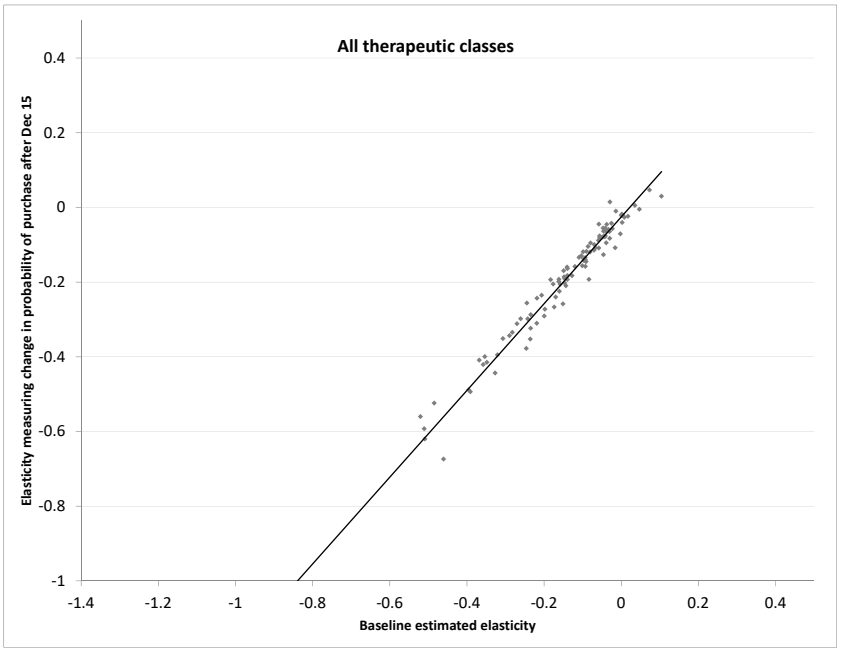
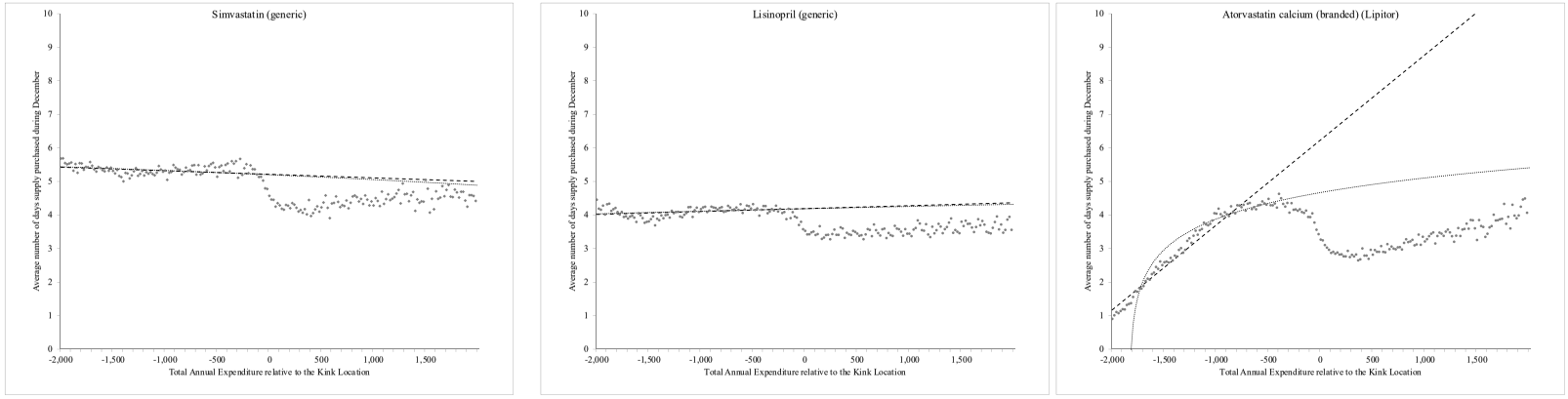



Figure shows the relationship between baseline elasticity estimates for common therapeutic classes and elasticity estimates that use alternative definitions of the end of year cutoffs (November and December in the top panel and the last two weeks of December in the bottom panel). The solid line mark unweighted OLS regressions relating the two elasticity measures.

Figure A14: Average number of drug days supply purchased in December

(a) Unconditional




(b) Conditional on making at least one claim

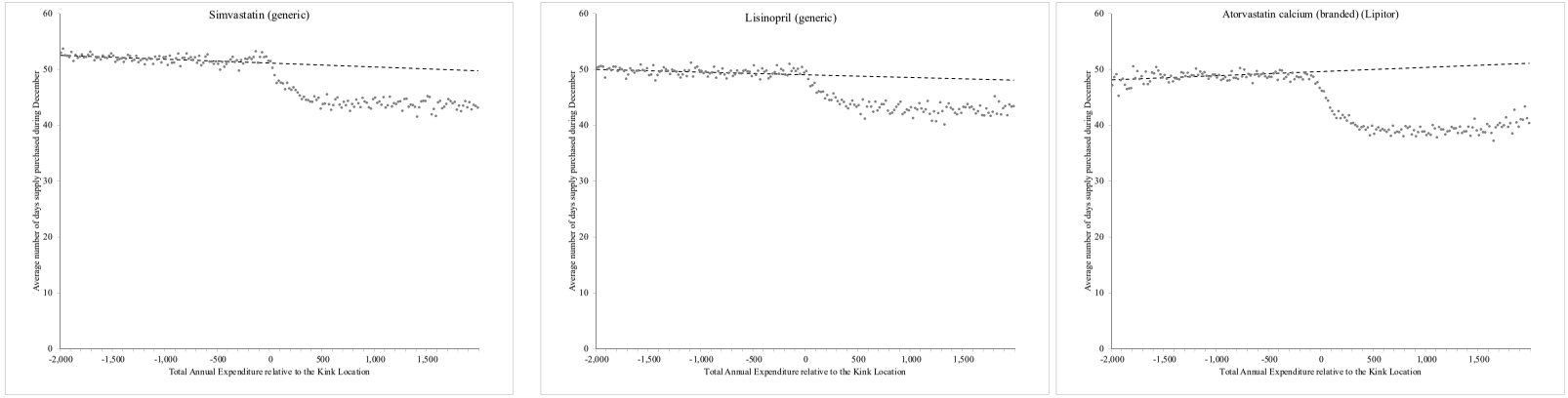
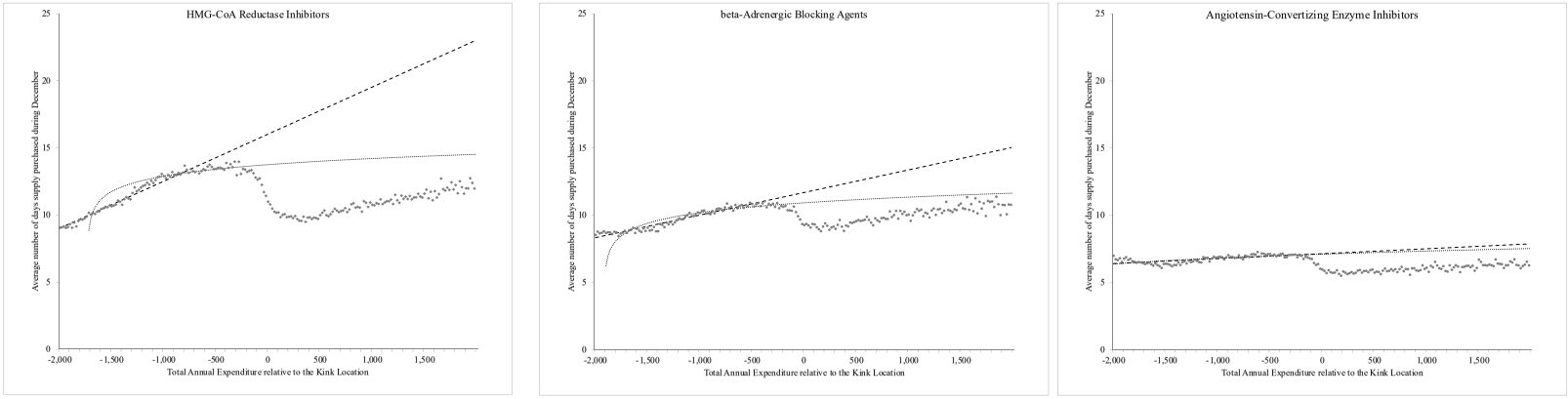



Figure shows the average number of days supply purchased in December for the top three "common" drugs. The top panel counts includes individuals that do not make any purchase of a given drug, setting the number of days supply purchased by these individuals to zero. The bottom panel only includes individuals that make at least one claim for a given drug in December. The horizontal axis is the individuals' total annual drug spending relative to the (year-specific) kink location in year $t$; we bin spending in \$20 bins. The vertical axis is the average number of days supply associated with the selected drug that were purchased by individuals within each bin in December of year $t$. A dashed line marks a counterfactual purchase quantity prediction using the linear fit in equation 9; a dotted line in the top panel marks a counterfactual purchase quantity prediction using the exponential fit in equation 10.

Figure A15: Average number of therapeutic class days supply purchased in December

(a) Unconditional




(b) Conditional on making at least one claim

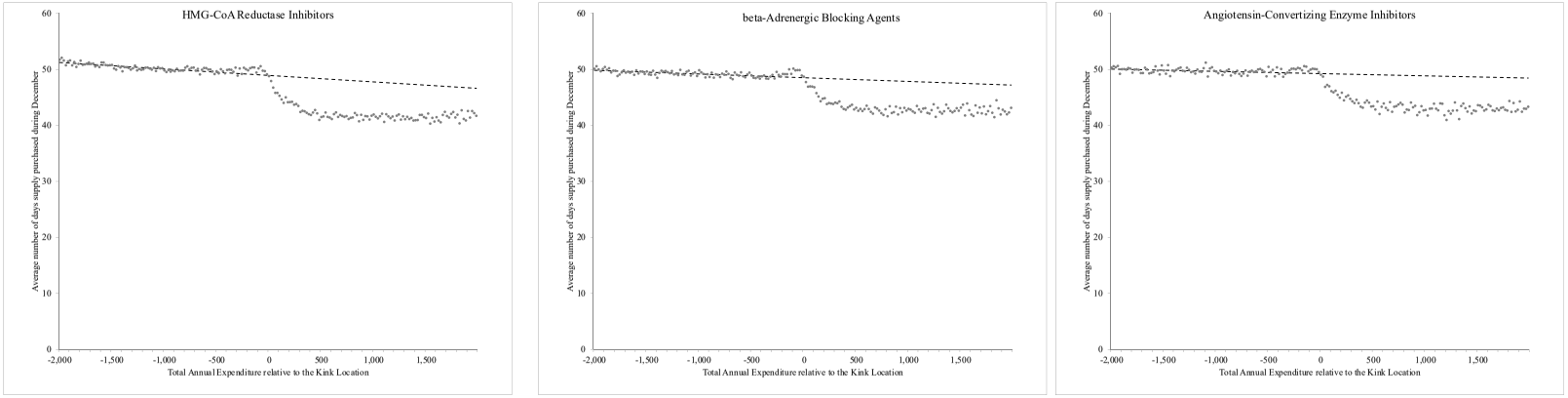
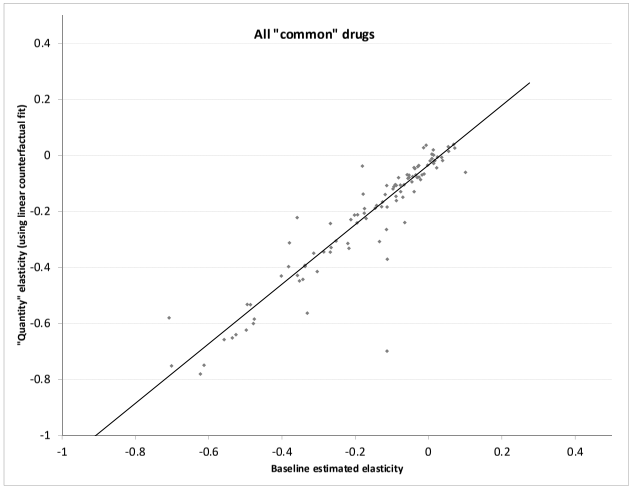


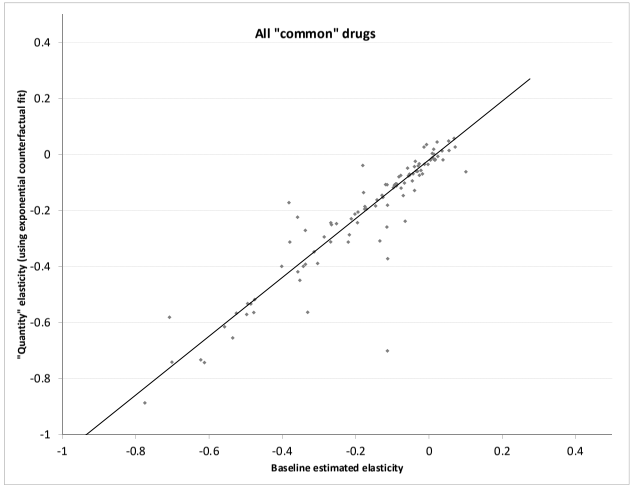

Figure shows the average number of days supply purchased in December for the top three "common" therapeutic classes. The top panel counts includes individuals that do not make any purchase of a given therapeutic class, setting the number of days supply purchased by these individuals to zero. The bottom panel only includes individuals that make at least one claim for a given therapeutic class in December. The horizontal axis is the individuals' total annual drug spending relative to the (year-specific) kink location in year $t$; we bin spending in \$20 bins. The vertical axis is the average number of days supply associated with the selected therapeutic class that were purchased by individuals within each bin in December of year $t$. A dashed line marks a counterfactual purchase quantity prediction using the linear fit in equation 9; a dotted line in the top panel marks a counterfactual purchase quantity prediction using the exponential fit in equation 10.

Figure A16: Correlation between baseline and "quantity" drug elasticities

(a) Unconditional, linear




(b) Unconditional, exponential




(c) Conditional

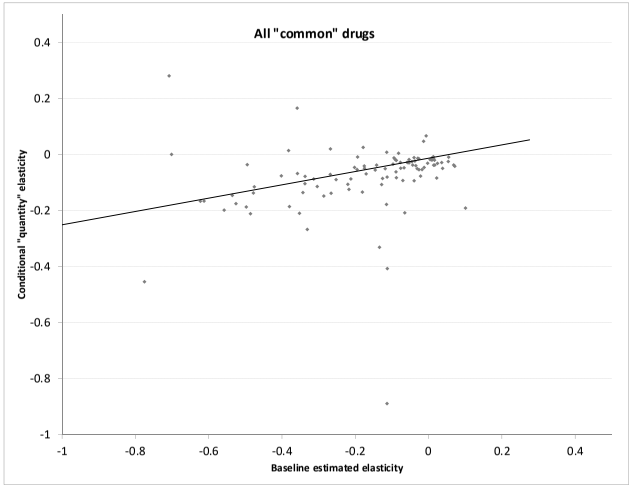
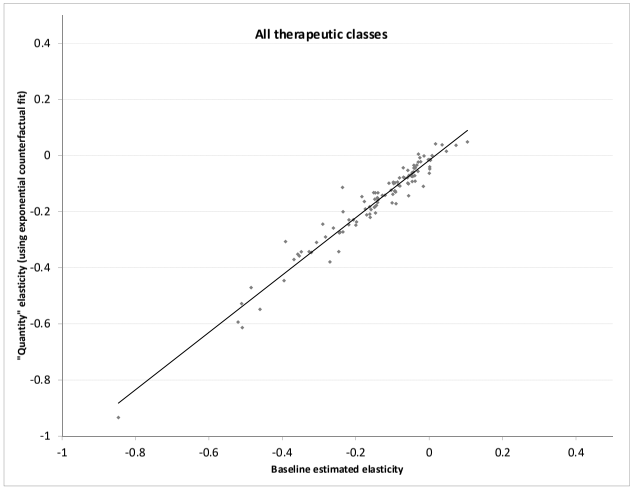


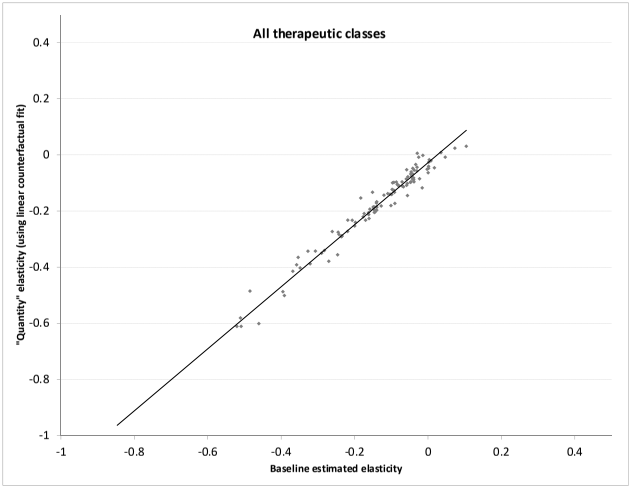

Figure shows the relationship between baseline elasticity estimates for common drugs and three types of quantity elasticity estimates. On the x-axis we record baseline elasticity estimates. On the y-axis we record quantity elasticity estimates. The three graphs report different measures of quantity elasticities as follows: (a) unconditional quantity elasticity using a linear counterfactual prediction; (b) unconditional quantity elasticity using an exponential counterfactual prediction, and (c) conditional quantity elasticity using a linear counterfactual prediction. The solid line marks unweighted OLS regressions relating each pair of elasticity measures.

Figure A17: Correlation between baseline and "quantity" therapeutic class elasticities

(a) Unconditional, linear




(b) Unconditional, exponential




(c) Conditional

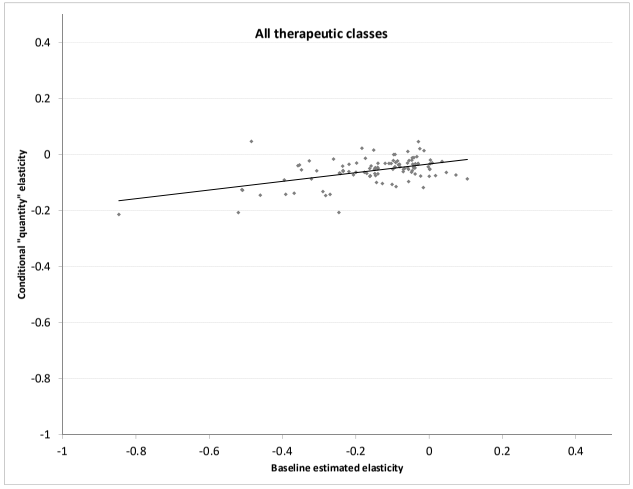



Figure shows the relationship between baseline elasticity estimates for common therapeutic classes and three types of quantity elasticity estimates. On the x-axis we record baseline elasticity estimates. On the y-axis we record quantity elasticity estimates. The three graphs report different measures of quantity elasticities as follows: (a) unconditional quantity elasticity using a linear counterfactual prediction; (b) unconditional quantity elasticity using an exponential counterfactual prediction, and (c) conditional quantity elasticity using a linear counterfactual prediction. The solid line marks unweighted OLS regressions relating each pair of elasticity measures.

Figure A18: Correlation between baseline elasticities and elasticities estimated on a sample of individuals in plans with no coverage in the gap

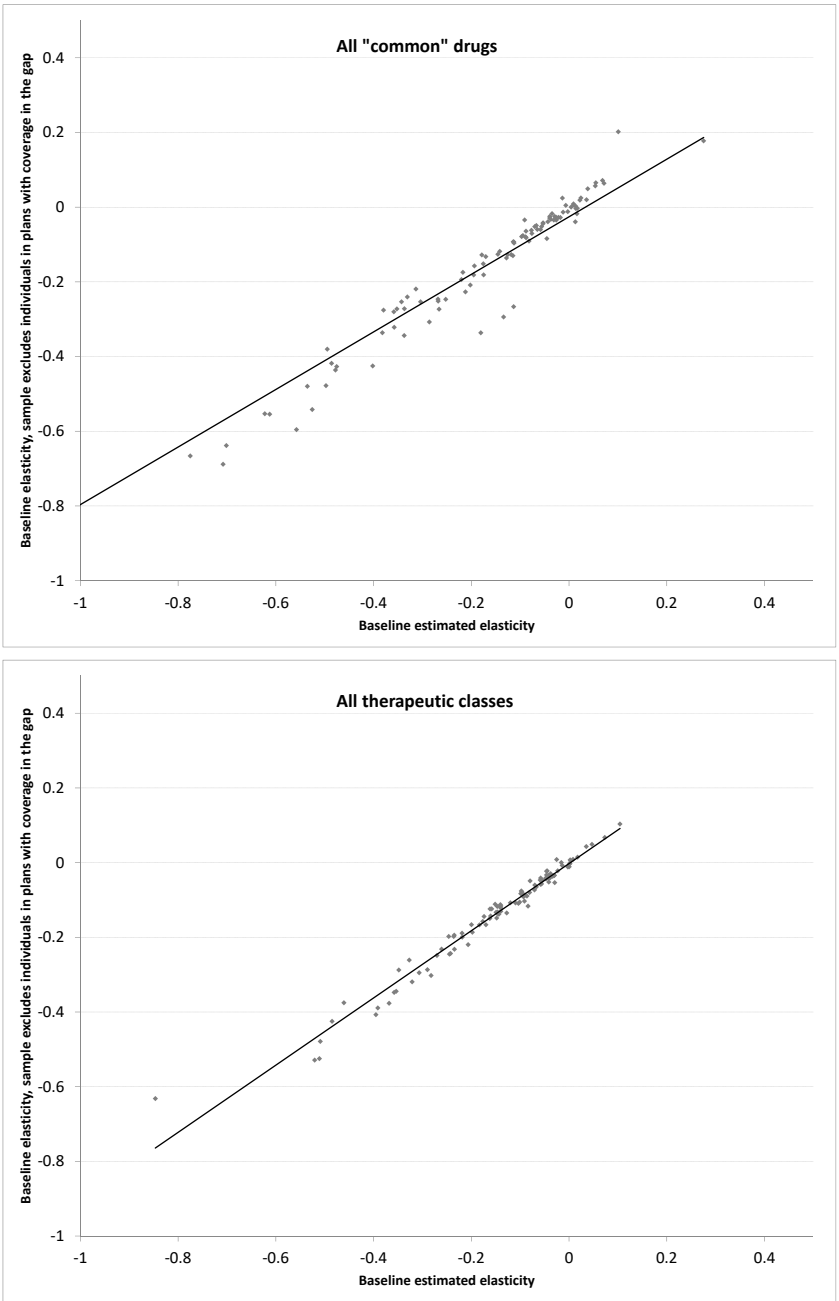



Figure shows the relationship between baseline elasticity estimates(x-axis) for common drugs (top panel) and therapeutic classes (bottom panel) and elasticity estimates done on a sample of individuals that were all enrolled in plans that did not provide any coverage in the gap (y-axis). The solid line marks unweighted OLS regressions relating each pair of elasticity measures.

Table A1: Cost-Sharing in Public Insurance across OECD Countries

| | Copayments | | | | | | | | Sources* |
|---|---|---|---|---|---|---|---|---|---|
| Country | Use of copayment | Vary by condition | Vary by type of drug | Vary by socio-economic state | Fixed or percentage | Maximum out –of-pocket limit (MOPL) | Cap | Deductible | |
| Australia | Yes | No | No | Yes | Fixed | Fixed, dependent on type of patient | No | No | [9,34–37] |
| Austria | Yes | No | No | No | Fixed | 2% of annual income | No | No | [10,38–40] |
| Belgium | Yes | Yes | No | Yes | Percentage | Dependent on type of patient | No | No | [41–45] |
| Canada | Varies by plan | No | No | Varies by plan | Varies by plan | Varies by plan | Varies by plan | Varies by plan | [7,46–51] |
| Czech Republic | Yes | Yes | No | Yes | Fixed | Set at 200€; for children under 18 and adults over 65, set at 100€ | No | No | [52,53] |
| Denmark | Yes | Yes | No | No | Both | Set at 406€ for chronically ill patients | No | Yes | [54,55] |
| England | Yes | Yes | No | Yes | Fixed | No | No | No | [45,56–59] |
| Estonia | Yes | Yes | No | Yes | Both | No | No | No | [60,61] |
| Finland | Yes | Yes | No | No | Percentage | Set at 672€; subsequent costs are reimbursed in full after a fixed 1.50€ copayment | No | No | [62–64] |
| France | Yes | No | No | No | Both | No | No | No | [45,65–67] |
| Germany | Yes | No | No | No | Both | Set at 2% of net income; 1% of net income for chronically ill patients | No | No | [45,68–72] |
| Greece | Yes | Yes | Yes | Yes | Percentage | No | No | No | [73,74] |
| Hungary | Yes | Yes | No | Yes | Percentage | No | No | No | [75,76] |
| Iceland | Yes | No | Yes | No | Percentage | No | No | No | [77] |
| Ireland** | Yes | No | No | No | Fixed | 19.50€ per month per family | No | No | [78–83] |
| Israel | Varies by plan | Varies by plan | Varies by plan | Varies by plan | Varies by plan | Varies by plan | No | No | [84,85] |
| Italy | Yes | Yes | No | Yes | Fixed | No | No | No | [45,86–88] |
| Japan | Yes | No | No | Yes | Percentage | Set at 80,000 yen monthly | No | No | [89–93] |
| Luxembourg | Yes | Yes | No | No | Percentage | 2.5% of net income | No | No | [94,95] |
| Mexico+ | No | | | | | No | No | No | [96,97] |
| Netherlands | Yes | No | No | No | Difference between reference price and retail | No | No | Yes | [45,98] |
| New Zealand | Yes | Yes | No | Yes | Fixed | No | No | No | [35,99–101] |
| Norway | Yes | Yes | No | Yes | Both | Set at 216€ and 63€ per prescription | No | No | [102] |
| Poland | Yes | Yes | No | No | Both | No | No | No | [103–105] |
| Portugal | Yes | No | Yes | No | Percentage | No | No | No | [106,107] |
| Scotland | No | | | | | | No | No | [57] |
| Slovakia | Yes | No | Yes | No | Both | No | No | No | [108,109] |
| Slovenia | Yes | Yes | No | Yes | Percentage | No | No | No | [105,110] |
| South Korea | Yes | Yes | No | Yes | Percentage | Set at 2, 3 or 4 million KRW depending on health insurance plan | No | No | [93,111–116] |
| Spain | Yes | Yes | No | Yes | Percentage | No | No | No | [45,117,118] |
| Sweden | Yes | No | Yes | No | Percentage | No | No | Yes | [22,119–123] |
| Switzerland | Yes | No | No | No | Percentage | Set at 700 CHF for adults and 350 CHF for children | Yes | Yes | [124,125] |
| Turkey | Yes | Yes | No | Yes | Percentage | No | No | No | [96,105,126] |
| US++ | Varies | No | No | No | | Copayment reduces to 5% after limit | Varies by plan. Step therapy, prior authorization and cost tiers | [127] | |

* in addition to system experts and agency websites.
** General Medical Services Scheme.
+Seguro Popular plan.
++Medicare.
doi:10.1371/journal.pone.0090434.t001

Table is a reproduction of Table 1 in **?**.

Table A2: Out-of-pocket costs, co-insurance, and formulary tiers

| Dependent Variable: | Mean OOP price ($US) | | | Mean total price ($US) | | | Mean co-insurance rate | | |
|---|---|---|---|---|---|---|---|---|---|
| Weighting: | Unweighted | Weighted by enrollment | Weighted by claims | Unweighted | Weighted by enrollment | Weighted by claims | Unweighted | Weighted by enrollment | Weighted by claims |
| | (1) | (2) | (3) | (4) | (5) | (6) | (4) | (5) | (6) |
| No. of Obs. | 26,448 | 26,448 | 26,448 | 26,448 | 26,448 | 26,448 | 26,448 | 26,448 | 26,448 |
| Mean of Dep. Var. | 57.9 | 75.52 | 16.85 | 179.8 | 233.9 | 53.67 | 0.338 | 0.35 | 0.297 |
| Std. Dev. Of Dep. Var. | 79.12 | 83.94 | 19.51 | 258.9 | 281.1 | 54.92 | 0.173 | 0.141 | 0.121 |
| **Panel A. High tier indicator:** | | | | | | | | | |
| High co-insurance (Tier 3) | 45.15 | 45.30 | 47.32 | 79.75 | 59.65 | 76.60 | 0.206 | 0.225 | 0.216 |
| | (4.86) | (7.86) | (5.05) | (19.22) | (23.00) | (13.56) | (0.025) | (0.023) | (0.037) |
| Plan Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.605 | 0.751 | 0.392 | 0.581 | 0.768 | 0.158 | 0.439 | 0.639 | 0.74 |
| **Panel B. Individual tier indicators:** | | | | | | | | | |
| Tier 1 | | | | | --- omitted --- | | | | |
| Tier 2 | 30.5 | 33.2 | 33.3 | 105.9 | 116.0 | 113.8 | 0.030 | -0.004 | 0.000 |
| | (3.6) | (4.0) | (2.1) | (11.3) | (15.2) | (4.8) | (0.023) | (0.016) | (0.012) |
| Tier 3 | 60.3 | 61.9 | 56.6 | 132.4 | 117.6 | 108.2 | 0.221 | 0.224 | 0.216 |
| | (4.6) | (5.7) | (3.4) | (18.2) | (14.3) | (5.6) | (0.028) | (0.025) | (0.037) |
| Tier 4 | 151.8 | 179.8 | 92.4 | 495.9 | 612.8 | 220.8 | 0.083 | 0.004 | 0.214 |
| | (12.0) | (10.4) | (8.8) | (46.0) | (34.6) | (41.7) | (0.029) | (0.018) | (0.064) |
| Tier 5 | 199.5 | 217.0 | 71.46 | 648.1 | 717.2 | 189.5 | 0.094 | -0.012 | 0.340 |
| | (22.8) | (19.4) | (36.8) | (89.3) | (67.2) | (136.1) | (0.06) | (0.024) | (0.152) |
| Tier 6 | 306.7 | 335.4 | 262.1 | 1,064.9 | 1,095.7 | 827.8 | -0.025 | -0.027 | 0.005 |
| | (20.1) | (24.9) | (25.8) | (85.7) | (89.1) | (74.7) | (0.089) | (0.057) | (0.053) |
| Plan Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.626 | 0.77 | 0.888 | 0.605 | 0.789 | 0.89 | 0.443 | 0.639 | 0.74 |

Table reports the relationship between average total cost, average out-of-pocket costs, and co-insurance rate across different tiers of part D plans. Panel A estimates the difference in the outcome variable by whether a drug is located in tiers 1-2 versus higher tiers. Panel B estimates the difference for each tier separately. In columns (1)-(3) the outcome variable is out-of-pocket drug cost, for any (not only common) drug. In Columns (4)-(6) the outcome variable is total cost. In columns (7)-(9) the outcome variable is the co-insurance; the co-insurance was computed at the individual claim level and then averaged within a plan-tier, which is the unit of observation. Plan enrollment weights (in columns (2), (5), and (8)) are computed using enrollees that make at least one claim for which out of pocket cost, total drug cost and co-insurance can be computed. The total cost, the out of pocket cost and the co-insurance were computed using only claims that fall above the deductible and below in the donut hole. Standard errors are clusterred at the insurer-tier level.

Table A3: Simulation results of the conceptual model

| | Social Planner | | Monopoly | | | | Duopoly (Lowest equilibrium[a]) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coins. | TS | Premium | Coins. | Profits | TS | Kappa | Premium | Coins. | Profits | TS |
| **Panel A: K=1** | | | | | | | | | | | |
| phi in (1,5) | 0.32 | 37.1 | 0.234 | 0.31 | 18.7 | 28.1 | 0.10 | 0.161 | 0.27 | 0.5 | 36.7 |
| | | | | | | | 0.40 | 0.195 | 0.27 | 11.2 | 35.4 |
| | | | | | | | 0.49 | 0.228 | 0.28 | 17.7 | 31.2 |
| phi in (5,9) | 0.17 | 135.8 | 0.378 | 0.22 | 92.7 | 129.6 | 0.10 | 0.249 | 0.12 | 8.3 | 134.9 |
| | | | | | | | 0.40 | 0.296 | 0.23 | 59.1 | 134.0 |
| | | | | | | | 0.49 | 0.356 | 0.23 | 88.3 | 134.2 |
| phi in (9,13) | 0.11 | 193.4 | 0.569 | 0.13 | 171.0 | 193.1 | 0.10 | 0.280 | 0.09 | 15.8 | 193.2 |
| | | | | | | | 0.40 | 0.470 | 0.09 | 110.8 | 193.2 |
| | | | | | | | 0.49 | 0.576 | 0.08 | 161.0 | 192.9 |
| **Panel B: K=1.5** | | | | | | | | | | | |
| phi in (1,5) | 0.24 | 89.1 | 0.367 | 0.25 | 46.3 | 66.2 | 0.10 | 0.233 | 0.16 | 3.9 | 87.7 |
| | | | | | | | 0.40 | 0.282 | 0.20 | 29.7 | 84.8 |
| | | | | | | | 0.49 | 0.354 | 0.19 | 43.7 | 74.7 |
| phi in (5,9) | 0.11 | 206.6 | 0.558 | 0.15 | 164.3 | 206.0 | 0.10 | 0.272 | 0.13 | 16.8 | 206.5 |
| | | | | | | | 0.40 | 0.467 | 0.13 | 114.3 | 206.5 |
| | | | | | | | 0.49 | 0.584 | 0.10 | 162.0 | 202.6 |
| phi in (9,13) | 0.07 | 255.7 | 0.732 | 0.09 | 237.7 | 255.6 | 0.10 | 0.399 | 0.04 | 59.3 | 255.0 |
| | | | | | | | 0.40 | 0.597 | 0.04 | 158.3 | 255.0 |
| | | | | | | | 0.49 | 0.730 | 0.06 | 229.6 | 255.6 |
| **Panel C: K=2** | | | | | | | | | | | |
| phi in (1,5) | 0.19 | 108.9 | 0.423 | 0.20 | 57.8 | 82.2 | 0.10 | 0.284 | 0.08 | 9.5 | 106.5 |
| | | | | | | | 0.40 | 0.355 | 0.14 | 45.1 | 100.7 |
| | | | | | | | 0.49 | 0.408 | 0.14 | 55.0 | 91.5 |
| phi in (5,9) | 0.09 | 224.8 | 0.615 | 0.13 | 185.5 | 224.0 | 0.10 | 0.304 | 0.08 | 19.5 | 224.8 |
| | | | | | | | 0.40 | 0.529 | 0.08 | 132.0 | 224.8 |
| | | | | | | | 0.49 | 0.646 | 0.08 | 180.6 | 215.0 |
| phi in (9,13) | 0.06 | 269.0 | 0.771 | 0.08 | 253.0 | 268.7 | 0.10 | 0.343 | 0.02 | 26.0 | 268.1 |
| | | | | | | | 0.40 | 0.625 | 0.03 | 169.2 | 268.6 |
| | | | | | | | 0.49 | 0.781 | 0.02 | 245.0 | 268.1 |

Table reports equilibrium results from the model described in Appendix A.

[a] In the duopoly case, in all cases considered, there exists an equilibrium in which both firms set the corresponding monopolist's premium and coinsurance rate.

Table A4: Relationship between drug level co-insurance and elasticity adjusted for inter-temporal substitution

| | Dependent Variable: Co-insurance rate | | | | | | |
|---|---|---|---|---|---|---|---|
| Sample | All drugs & plans | All drugs & plans | High frequency drugs | All drugs & plans | "Lower subst." drugs | Branded drugs | Generic drugs |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Panel A. Baseline elasticity estimates** | | | | | | | |
| Estimated demand elasticity | -0.283 | -0.284 | -0.336 | -0.236 | -0.315 | -0.264 | -0.619 |
| | (0.044) | (0.044) | (0.081) | (0.037) | (0.098) | (0.032) | (0.075) |
| Plan fixed effects | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes | No | No | No |
| R-squared | 0.083 | 0.342 | 0.370 | 0.426 | 0.493 | 0.303 | 0.518 |
| No. of Obs. (plan years) | 654,270 | 654,270 | 521,358 | 654,270 | 139,965 | 277,684 | 376,586 |
| Mean od Dep. Var. | 0.435 | 0.435 | 0.441 | 0.435 | 0.485 | 0.400 | 0.462 |
| Std. Dev. Of Dep. Var. | 0.306 | 0.306 | 0.304 | 0.306 | 0.339 | 0.266 | 0.33 |
| **Panel B. Baseline elasticity estimates on I/S sample** | | | | | | | |
| Estimated demand elasticity | -0.263 | -0.264 | -0.315 | -0.219 | -0.293 | -0.251 | -0.548 |
| | (0.042) | (0.042) | (0.078) | (0.035) | (0.092) | (0.032) | (0.080) |
| Plan fixed effects | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes | No | No | No |
| R-squared | 0.079 | 0.338 | 0.366 | 0.423 | 0.488 | 0.301 | 0.506 |
| No. of Obs. (plan years) | 654,270 | 654,270 | 521,358 | 654,270 | 139,965 | 277,684 | 376,586 |
| Mean od Dep. Var. | 0.435 | 0.435 | 0.441 | 0.435 | 0.485 | 0.400 | 0.462 |
| Std. Dev. Of Dep. Var. | 0.306 | 0.306 | 0.304 | 0.306 | 0.339 | 0.266 | 0.33 |
| **Panel C. I/S-adjusted elasticity estimates** | | | | | | | |
| Estimated demand elasticity | -0.223 | -0.224 | -0.317 | -0.177 | -0.407 | -0.208 | -0.462 |
| | (0.045) | (0.045) | (0.096) | (0.038) | (0.121) | (0.052) | (0.132) |
| Plan fixed effects | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes | No | No | No |
| R-squared | 0.040 | 0.299 | 0.330 | 0.394 | 0.477 | 0.211 | 0.468 |
| No. of Obs. (plan years) | 654,270 | 654,270 | 521,358 | 654,270 | 139,965 | 277,684 | 376,586 |
| Mean od Dep. Var. | 0.435 | 0.435 | 0.441 | 0.435 | 0.485 | 0.400 | 0.462 |
| Std. Dev. Of Dep. Var. | 0.306 | 0.306 | 0.304 | 0.306 | 0.339 | 0.266 | 0.33 |

Table shows the relationship between a drug's pre-gap co-insurance rate and its estimated elasticity. Panel A repeats the baseline results using baseline elasticity estimates. Panel B uses baseline elasticities estimated on the inter-temporal substitution sample. Panel C uses elasticity estimates adjusted for inter-temporal substitution. The unit of observation is a drug by plan. Standard errors in parentheses are clustered at the drug level.

Table A5: Relationship between therapeutic classes level co-insurance and elasticity adjusted for inter-temporal substitution

| | Dependent Variable: Co-insurance rate | | | |
|---|---|---|---|---|
| Sample | All classes & plans | All classes & plans | High frequency classes | All classes & plans |
| | (1) | (2) | (3) | (4) |
| **Panel A. Baseline elasticity estimates** | | | | |
| Estimated demand elasticity | -0.308 | -0.310 | -0.316 | -0.256 |
| | (0.064) | (0.065) | (0.074) | (0.053) |
| Plan fixed effects | No | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes |
| R-squared | 0.030 | 0.305 | 0.34 | 0.387 |
| No. of Obs. (plan years) | 587,050 | 587,050 | 463,507 | 587,050 |
| Mean od Dep. Var. | 0.408 | 0.408 | 0.416 | 0.408 |
| Std. Dev. Of Dep. Var. | 0.267 | 0.267 | 0.267 | 0.267 |
| **Panel B. Baseline elasticity estimates on I/S sample** | | | | |
| Estimated demand elasticity | -0.294 | -0.296 | -0.302 | -0.243 |
| | (0.064) | (0.064) | (0.073) | (0.052) |
| Plan fixed effects | No | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes |
| R-squared | 0.028 | 0.304 | 0.339 | 0.385 |
| No. of Obs. (plan years) | 587,050 | 587,050 | 463,507 | 587,050 |
| Mean od Dep. Var. | 0.408 | 0.408 | 0.416 | 0.408 |
| Std. Dev. Of Dep. Var. | 0.267 | 0.267 | 0.267 | 0.267 |
| **Panel C. I/S-adjusted elasticity estimates** | | | | |
| Estimated demand elasticity | -0.367 | -0.370 | -0.364 | -0.260 |
| | (0.083) | (0.084) | (0.104) | (0.065) |
| Plan fixed effects | No | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes |
| R-squared | 0.025 | 0.300 | 0.331 | 0.379 |
| No. of Obs. (plan years) | 587,050 | 587,050 | 463,507 | 587,050 |
| Mean od Dep. Var. | 0.408 | 0.408 | 0.416 | 0.408 |
| Std. Dev. Of Dep. Var. | 0.267 | 0.267 | 0.267 | 0.267 |

Table shows the relationship between a therapeutic class' pre-gap co-insurance rate and its estimated elasticity. Panel A repeats the baseline results using baseline elasticity estimates. Panel B uses baseline elasticities estimated on the inter-temporal substitution sample. Panel C uses elasticity estimates adjusted for inter-temporal substitution. The unit of observation is a therapeutic class by plan. Standard errors in parentheses are clustered at the class level.

Table A6: Relationship between co-insurance and elasticities estimated on a sample of individuals with no deductibles in $t+1$

| | Dependent Variable: Co-insurance rate | | | | | | |
|---|---|---|---|---|---|---|---|
| Sample | All drugs & plans | All drugs & plans | High frequency drugs | All drugs & plans | "Lower subst." drugs | Branded drugs | Generic drugs |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Panel A. Drug-level analysis** | | | | | | | |
| Estimated demand elasticity | -0.040 | -0.040 | -0.152 | -0.031 | 0.019 | -0.021 | -0.444 |
| | (0.053) | (0.054) | (0.056) | (0.044) | (0.031) | (0.050) | (0.052) |
| Plan fixed effects | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes | No | No | No |
| R-squared | 0.010 | 0.268 | 0.354 | 0.375 | 0.372 | 0.128 | 0.524 |
| No. of Obs. (plan years) | 654,270 | 654,270 | 521,358 | 654,270 | 139,965 | 277,684 | 376,586 |
| Mean of Dep. Var. | 0.435 | 0.435 | 0.441 | 0.435 | 0.485 | 0.400 | 0.462 |
| Std. Dev. Of Dep. Var. | 0.306 | 0.306 | 0.304 | 0.306 | 0.339 | 0.266 | 0.33 |
| **Panel B. Class-level analysis** | | | | | | | |
| Estimated demand elasticity | -0.225 | -0.227 | -0.214 | -0.185 | | | |
| | (0.054) | (0.054) | (0.057) | (0.048) | | | |
| Plan fixed effects | No | Yes | Yes | Yes | | | |
| Drug price included | No | No | No | Yes | | | |
| R-squared | 0.035 | 0.31 | 0.342 | 0.389 | | | |
| No. of Obs. (plan years) | 587,050 | 587,050 | 463,507 | 587,050 | | | |
| Mean od Dep. Var. | 0.408 | 0.408 | 0.416 | 0.408 | | | |
| Std. Dev. Of Dep. Var. | 0.267 | 0.267 | 0.267 | 0.267 | | | |

Table shows the relationship between a drug's (Panel A) of therapeutic class' (Panel B) pre-gap co-insurance rate and its estimated elasticity. Elasticities are estimated on a sub-sample of individuals enrolled in plans with no deductibles in the following year. Unit of observation is a drug (or class) by plan. Standard errors in parentheses are clustered at the drug (or class) levels.

Table A7: Relationship between drug level co-insurance and elasticities estimated under alternative end of year definitions

| | Dependent Variable: Co-insurance rate | | | | | | |
|---|---|---|---|---|---|---|---|
| Sample | All drugs & plans | All drugs & plans | High frequency drugs | All drugs & plans | "Lower subst." drugs | Branded drugs | Generic drugs |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Panel A. End of year interval November and December** | | | | | | | |
| Estimated demand elasticity | -0.314 | -0.315 | -0.361 | -0.256 | -0.433 | -0.307 | -0.601 |
| | (0.049) | (0.050) | (0.083) | (0.041) | (0.110) | (0.041) | (0.114) |
| Plan fixed effects | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes | No | No | No |
| R-squared | 0.068 | 0.326 | 0.355 | 0.413 | 0.496 | 0.282 | 0.487 |
| No. of Obs. (plan years) | 654,270 | 654,270 | 521,358 | 654,270 | 139,965 | 277,684 | 376,586 |
| Mean od Dep. Var. | 0.435 | 0.435 | 0.441 | 0.435 | 0.485 | 0.400 | 0.462 |
| Std. Dev. Of Dep. Var. | 0.306 | 0.306 | 0.304 | 0.306 | 0.339 | 0.266 | 0.33 |
| **Panel A. End of year interval December 15 - December 31** | | | | | | | |
| Estimated demand elasticity | -0.208 | -0.209 | -0.290 | -0.173 | -0.237 | -0.188 | -0.534 |
| | (0.037) | (0.038) | (0.080) | (0.032) | (0.082) | (0.030) | (0.064) |
| Plan fixed effects | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes | No | No | No |
| R-squared | 0.077 | 0.336 | 0.380 | 0.421 | 0.491 | 0.284 | 0.527 |
| No. of Obs. (plan years) | 654,270 | 654,270 | 521,358 | 654,270 | 139,965 | 277,684 | 376,586 |
| Mean od Dep. Var. | 0.435 | 0.435 | 0.441 | 0.435 | 0.485 | 0.400 | 0.462 |
| Std. Dev. Of Dep. Var. | 0.306 | 0.306 | 0.304 | 0.306 | 0.339 | 0.266 | 0.33 |

Table shows the relationship between a drug's pre-gap co-insurance rate and its estimated elasticity. Panel A uses elasticity estimates based on the change in the probability of claiming a given drug in November and December. Panel B uses elasticity estimates based on claims between December 15 and December 31. Unit of observation is a drug by plan. Standard errors in parentheses are clustered at the drug level.

Table A8: Relationship between therapeutic class level co-insurance and elasticities estimated under alternative end of year definitions

| | Dependent Variable: Co-insurance rate | | | |
|---|---|---|---|---|
| Sample | All classes & plans | All classes & plans | High frequency classes | All classes & plans |
| | (1) | (2) | (3) | (4) |
| **Panel A. End of year interval November and December** | | | | |
| Estimated demand elasticity | -0.319 | -0.321 | -0.350 | -0.249 |
| | (0.078) | (0.079) | (0.089) | (0.061) |
| Plan fixed effects | No | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes |
| R-squared | 0.022 | 0.297 | 0.335 | 0.380 |
| No. of Obs. (plan years) | 587,050 | 587,050 | 463,507 | 587,050 |
| Mean od Dep. Var. | 0.408 | 0.408 | 0.416 | 0.408 |
| Std. Dev. Of Dep. Var. | 0.267 | 0.267 | 0.267 | 0.267 |
| **Panel A. End of year interval December 15 - December 31** | | | | |
| Estimated demand elasticity | -0.286 | -0.288 | -0.285 | -0.239 |
| | (0.059) | (0.059) | (0.066) | (0.051) |
| Plan fixed effects | No | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes |
| R-squared | 0.037 | 0.313 | 0.347 | 0.392 |
| No. of Obs. (plan years) | 587,050 | 587,050 | 463,507 | 587,050 |
| Mean od Dep. Var. | 0.408 | 0.408 | 0.416 | 0.408 |
| Std. Dev. Of Dep. Var. | 0.267 | 0.267 | 0.267 | 0.267 |

Table shows the relationship between a therapeutic class' pre-gap co-insurance rate and its estimated elasticity. Panel A uses elasticity estimates based on the change in the probability of claiming a drug in a given therapeutic class in November and December. Panel B uses elasticity estimates based on claims between December 15 and December 31. Unit of observation is a therapeutic class by plan. Standard errors in parentheses are clustered at the class level.

Table A9: Relationship between drug level co-insurance and "quantity" elasticities

| | Dependent Variable: Co-insurance rate | | | | | | |
|---|---|---|---|---|---|---|---|
| Sample | All drugs & plans | All drugs & plans | High frequency drugs | All drugs & plans | "Lower subst." drugs | Branded drugs | Generic drugs |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Panel A. Unconditional quantity elasticity, linear predictions** | | | | | | | |
| Estimated demand elasticity | -0.246 | -0.247 | -0.287 | -0.205 | -0.246 | -0.224 | -0.558 |
| | (0.042) | (0.042) | (0.073) | (0.035) | (0.077) | (0.029) | (0.066) |
| Plan fixed effects | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes | No | No | No |
| R-squared | 0.088 | 0.346 | 0.373 | 0.429 | 0.484 | 0.303 | 0.530 |
| No. of Obs. (plan years) | 654,270 | 654,270 | 521,358 | 654,270 | 139,965 | 277,684 | 376,586 |
| Mean od Dep. Var. | 0.435 | 0.435 | 0.441 | 0.435 | 0.485 | 0.400 | 0.462 |
| Std. Dev. Of Dep. Var. | 0.306 | 0.306 | 0.304 | 0.306 | 0.339 | 0.266 | 0.33 |
| **Panel B. Unconditional quantity elasticity, exponential predictions** | | | | | | | |
| Estimated demand elasticity | -0.256 | -0.257 | -0.311 | -0.210 | -0.24 | -0.228 | -0.552 |
| | (0.042) | (0.042) | (0.074) | (0.035) | (0.072) | (0.030) | (0.066) |
| Plan fixed effects | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes | No | No | No |
| R-squared | 0.087 | 0.345 | 0.375 | 0.426 | 0.477 | 0.294 | 0.524 |
| No. of Obs. (plan years) | 654,270 | 654,270 | 521,358 | 654,270 | 139,965 | 277,684 | 376,586 |
| Mean od Dep. Var. | 0.435 | 0.435 | 0.441 | 0.435 | 0.485 | 0.400 | 0.462 |
| Std. Dev. Of Dep. Var. | 0.306 | 0.306 | 0.304 | 0.306 | 0.339 | 0.266 | 0.33 |
| **Panel C. Conditional quantity elasticity, linear predictions** | | | | | | | |
| Estimated demand elasticity | -0.439 | -0.437 | -0.720 | -0.405 | -0.560 | -0.396 | -1.118 |
| | (0.114) | (0.115) | (0.229) | (0.100) | (0.153) | (0.122) | (0.540) |
| Plan fixed effects | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes | No | No | No |
| R-squared | 0.033 | 0.291 | 0.331 | 0.397 | 0.411 | 0.188 | 0.477 |
| No. of Obs. (plan years) | 654,270 | 654,270 | 521,358 | 654,270 | 139,965 | 277,684 | 376,586 |
| Mean od Dep. Var. | 0.435 | 0.435 | 0.441 | 0.435 | 0.485 | 0.400 | 0.462 |
| Std. Dev. Of Dep. Var. | 0.306 | 0.306 | 0.304 | 0.306 | 0.339 | 0.266 | 0.33 |

Table shows the relationship between a drug's pre-gap co-insurance rate and its estimated elasticity. Panel A uses unconditional quantity elasticities, estimated using a linear counterfactual prediction. Panel B uses unconditional quantity elasticities, estimated using an exponential counterfactual prediction. Panel C uses conditional quantity elasticities (conditional on having at least one purchase of the drug), estimated using a linear counterfactual prediction. The unit of observation is a drug by plan. Standard errors in parentheses are clustered at the drug level.

Table A10: Relationship between therapeutic class level co-insurance and "quantity" elasticities

| | Dependent Variable: Co-insurance rate | | | |
|---|---|---|---|---|
| Sample | All classes & plans | All classes & plans | High frequency classes | All classes & plans |
| | (1) | (2) | (3) | (4) |
| **Panel A. Unconditional quantity elasticity, linear predictions** | | | | |
| Estimated demand elasticity | -0.285 | -0.287 | -0.286 | -0.239 |
| | (0.058) | (0.059) | (0.066) | (0.049) |
| Plan fixed effects | No | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes |
| R-squared | 0.033 | 0.308 | 0.343 | 0.389 |
| No. of Obs. (plan years) | 587,050 | 587,050 | 463,507 | 587,050 |
| Mean od Dep. Var. | 0.408 | 0.408 | 0.416 | 0.408 |
| Std. Dev. Of Dep. Var. | 0.267 | 0.267 | 0.267 | 0.267 |
| **Panel B. Unconditional quantity elasticity, exponential predictions** | | | | |
| Estimated demand elasticity | -0.304 | -0.304 | -0.313 | -0.244 |
| | (0.060) | (0.060) | (0.069) | (0.049) |
| Plan fixed effects | No | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes |
| R-squared | 0.032 | 0.307 | 0.343 | 0.387 |
| No. of Obs. (plan years) | 587,050 | 587,050 | 463,507 | 587,050 |
| Mean od Dep. Var. | 0.408 | 0.408 | 0.416 | 0.408 |
| Std. Dev. Of Dep. Var. | 0.267 | 0.267 | 0.267 | 0.267 |
| **Panel C. Conditional quantity elasticity, linear predictions** | | | | |
| Estimated demand elasticity | -0.578 | -0.570 | -0.702 | -0.722 |
| | (0.273) | (0.278) | (0.373) | (0.199) |
| Plan fixed effects | No | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes |
| R-squared | 0.009 | 0.284 | 0.318 | 0.380 |
| No. of Obs. (plan years) | 587,050 | 587,050 | 463,507 | 587,050 |
| Mean od Dep. Var. | 0.408 | 0.408 | 0.416 | 0.408 |
| Std. Dev. Of Dep. Var. | 0.267 | 0.267 | 0.267 | 0.267 |

Table shows the relationship between a therapeutic class' pre-gap co-insurance rate and its estimated elasticity. Panel A uses unconditional quantity elasticities, estimated using a linear counterfactual prediction. Panel B uses unconditional quantity elasticities, estimated using an exponential counterfactual prediction. Panel C uses conditional quantity elasticities (conditional on having at least one purchase in the given therapeutic class), estimated using a linear counterfactual prediction. The unit of observation is a therapeutic class by plan. Standard errors in parentheses are clustered at the class level.

Table A11: Relationship between co-insurance and elasticities estimated on a sample of individuals in plans with no coverage in the gap

| | Dependent Variable: Co-insurance rate | | | | | | |
|---|---|---|---|---|---|---|---|
| Sample | All drugs & plans | All drugs & plans | High frequency drugs | All drugs & plans | "Lower subst." drugs | Branded drugs | Generic drugs |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Panel A. Drug-level analysis** | | | | | | | |
| Estimated demand elasticity | -0.302 | -0.304 | -0.418 | -0.257 | -0.489 | -0.273 | -0.700 |
| | (0.071) | (0.070) | (0.065) | (0.060) | (0.105) | (0.079) | (0.091) |
| Plan fixed effects | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes | No | No | No |
| R-squared | 0.069 | 0.328 | 0.373 | 0.419 | 0.514 | 0.261 | 0.518 |
| No. of Obs. (plan years) | 654,270 | 654,270 | 521,358 | 654,270 | 139,965 | 277,684 | 376,586 |
| Mean of Dep. Var. | 0.435 | 0.435 | 0.441 | 0.435 | 0.485 | 0.400 | 0.462 |
| Std. Dev. Of Dep. Var. | 0.306 | 0.306 | 0.304 | 0.306 | 0.339 | 0.266 | 0.33 |
| **Panel B. Class-level analysis** | | | | | | | |
| Estimated demand elasticity | -0.328 | -0.329 | -0.334 | -0.286 | | | |
| | (0.074) | (0.076) | (0.087) | (0.057) | | | |
| Plan fixed effects | No | Yes | Yes | Yes | | | |
| Drug price included | No | No | No | Yes | | | |
| R-squared | 0.028 | 0.303 | 0.337 | 0.387 | | | |
| No. of Obs. (plan years) | 587,050 | 587,050 | 463,507 | 587,050 | | | |
| Mean od Dep. Var. | 0.408 | 0.408 | 0.416 | 0.408 | | | |
| Std. Dev. Of Dep. Var. | 0.267 | 0.267 | 0.267 | 0.267 | | | |

Table shows the relationship between a drug's (Panel A) of therapeutic class' (Panel B) pre-gap co-insurance rate and its estimated elasticity. Elasticities are estimated on a sub-sample of individuals enrolled in plans with no coverage in the gap. Unit of observation is a drug (or class) by plan. Standard errors in parentheses are clustered at the drug (or class) levels.

Table A12: Relationship between co-insurance and elasticity with plan-level leave-one-out elasticities

| | Dependent Variable: Co-insurance rate | | | | | | |
|---|---|---|---|---|---|---|---|
| Sample | All drugs & plans | All drugs & plans | High frequency drugs | All drugs & plans | "Lower subst." drugs | Branded drugs | Generic drugs |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Panel A. Drug-level analysis** | | | | | | | |
| Estimated demand elasticity | -0.282 | -0.284 | -0.336 | -0.235 | -0.315 | -0.264 | -0.618 |
| | (0.043) | (0.044) | (0.081) | (0.037) | (0.098) | (0.032) | (0.075) |
| Plan fixed effects | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes | No | No | No |
| R-squared | 0.083 | 0.342 | 0.370 | 0.426 | 0.493 | 0.303 | 0.518 |
| No. of Obs. (plan years) | 654,270 | 654,270 | 521,358 | 654,270 | 139,965 | 277,684 | 376,586 |
| Mean of Dep. Var. | 0.435 | 0.435 | 0.441 | 0.435 | 0.485 | 0.400 | 0.462 |
| Std. Dev. Of Dep. Var. | 0.306 | 0.306 | 0.304 | 0.306 | 0.339 | 0.266 | 0.33 |
| **Panel B. Class-level analysis** | | | | | | | |
| Estimated demand elasticity | -0.385 | -0.386 | -0.391 | -0.323 | | | |
| | (0.076) | (0.077) | (0.090) | (0.060) | | | |
| Plan fixed effects | No | Yes | Yes | Yes | | | |
| Drug price included | No | No | No | Yes | | | |
| R-squared | 0.035 | 0.311 | 0.344 | 0.391 | | | |
| No. of Obs. (plan years) | 587,050 | 587,050 | 463,507 | 587,050 | | | |
| Mean od Dep. Var. | 0.408 | 0.408 | 0.416 | 0.408 | | | |
| Std. Dev. Of Dep. Var. | 0.267 | 0.267 | 0.267 | 0.267 | | | |

Table shows the relationship between a drug's (Panel A) or class' (Panel B) pre-gap co-insurance rate and the estimated plan-level leave-one out elasticity. The unit of observation is a drug (or class) by plan. Standard errors in parentheses are clustered at the drug (or class) levels.

Table A13: Relationship between co-insurance and elasticity with insurer-level leave-one-out elasticities

| | Dependent Variable: Co-insurance rate | | | | | | |
|---|---|---|---|---|---|---|---|
| Sample | All drugs & plans | All drugs & plans | High frequency drugs | All drugs & plans | "Lower subst." drugs | Branded drugs | Generic drugs |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Panel A. Drug-level analysis** | | | | | | | |
| Estimated demand elasticity | -0.128 | -0.134 | -0.317 | -0.110 | -0.221 | -0.116 | -0.589 |
| | (0.041) | (0.043) | (0.077) | (0.034) | (0.081) | (0.039) | (0.072) |
| Plan fixed effects | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Drug price included | No | No | No | Yes | No | No | No |
| R-squared | 0.039 | 0.300 | 0.365 | 0.398 | 0.460 | 0.208 | 0.514 |
| No. of Obs. (plan years) | 654,270 | 654,270 | 521,358 | 654,270 | 139,965 | 277,684 | 376,586 |
| Mean of Dep. Var. | 0.435 | 0.435 | 0.441 | 0.435 | 0.485 | 0.400 | 0.462 |
| Std. Dev. Of Dep. Var. | 0.306 | 0.306 | 0.304 | 0.306 | 0.339 | 0.266 | 0.33 |
| **Panel B. Class-level analysis** | | | | | | | |
| Estimated demand elasticity | -0.298 | -0.308 | -0.314 | -0.255 | | | |
| | (0.063) | (0.065) | (0.073) | (0.052) | | | |
| Plan fixed effects | No | Yes | Yes | Yes | | | |
| Drug price included | No | No | No | Yes | | | |
| R-squared | 0.028 | 0.305 | 0.339 | 0.386 | | | |
| No. of Obs. (plan years) | 587,050 | 587,050 | 463,507 | 587,050 | | | |
| Mean od Dep. Var. | 0.408 | 0.408 | 0.416 | 0.408 | | | |
| Std. Dev. Of Dep. Var. | 0.267 | 0.267 | 0.267 | 0.267 | | | |

Table shows the relationship between a drug's (Panel A) or class' (Panel B) pre-gap co-insurance rate and the estimated contract-level leave-one out elasticity. The unit of observation is a drug (or class) by plan. Standard errors in parentheses are clustered at the drug (or class) levels.

Table A14: Baseline Estimated Elasticities for All "Common" Therapeutic Classes

| Therapeutic class name (1) | AHFS code (2) | Claim share (3) | Spend share (4) | %ΔQ (5) | %ΔOOP (6) | Elasticity (7) |
|---|---|---|---|---|---|---|
| All common therapeutic classes | - | 0.860 | 0.847 | -10.2 | 234.4 | -0.04 |
| HMG-CoA Reductase Inhibitors^ | 24060800 | 0.077 | 0.097 | -31.9 | 136.1 | -0.23 |
| beta-Adrenergic Blocking Agents^ | 24240000 | 0.067 | 0.028 | -17.5 | 125.5 | -0.14 |
| Angiotensin-Converting Enzyme Inhibitors^ | 24320400 | 0.047 | 0.013 | -14.1 | 87.7 | -0.16 |
| Thiazide Diuretics^ | 40282000 | 0.045 | 0.027 | -27.0 | 84.2 | -0.32 |
| Thyroid Agents^ | 68360400 | 0.038 | 0.008 | -18.1 | 21.4 | -0.85 |
| Dihydropyridines^ | 24280800 | 0.031 | 0.016 | -19.5 | 138.0 | -0.14 |
| Proton-pump Inhibitors^ | 56283600 | 0.030 | 0.047 | -26.6 | 243.0 | -0.11 |
| Selective Serotonin-reuptake Inhibitors^ | 28160420 | 0.023 | 0.015 | -16.4 | 111.5 | -0.15 |
| Angiotensin II Receptor Antagonists^ | 24320800 | 0.022 | 0.034 | -29.3 | 74.8 | -0.39 |
| Opiate Agonists | 28080800 | 0.022 | 0.009 | -5.5 | 131.9 | -0.04 |
| Loop Diuretics^ | 40280800 | 0.022 | 0.002 | -11.2 | 47.5 | -0.24 |
| Coumarin Derivatives^ | 20120408 | 0.019 | 0.006 | -20.6 | 59.0 | -0.35 |
| Biguanides^ | 68200400 | 0.016 | 0.006 | -8.9 | 133.7 | -0.07 |
| Bone Resorption Inhibitors^ | 92240000 | 0.016 | 0.017 | -41.1 | 114.8 | -0.36 |
| Platelet-Aggregation Inhibitors^ | 20121800 | 0.016 | 0.049 | 3.9 | 221.2 | 0.02 |
| Replacement Preparations^ | 40120000 | 0.015 | 0.005 | -14.3 | 146.8 | -0.10 |
| Sulfonylureas^ | 68202000 | 0.013 | 0.004 | -0.3 | 110.0 | 0.00 |
| Anxiolytics, Sedatives, and Hypnotics; Miscellaneous | 28249200 | 0.013 | 0.008 | -12.2 | 150.9 | -0.08 |
| Other Nonsteroidal Anti-inflammatory Agents^ | 28080492 | 0.012 | 0.005 | -20.0 | 136.3 | -0.15 |
| Selective beta-2-Adrenergic Agonists^ | 12120812 | 0.011 | 0.028 | -14.9 | 211.0 | -0.07 |
| Anticonvulsants, Miscellaneous^ | 28129200 | 0.011 | 0.013 | -8.8 | 209.1 | -0.04 |
| Calcium-Channel Blocking Agents, Miscellaneous^ | 24289200 | 0.010 | 0.007 | -15.9 | 269.8 | -0.06 |
| Adrenals | 68040000 | 0.009 | 0.006 | -7.2 | 150.9 | -0.05 |
| Parasympathomimetic (Cholinergic) Agents^ | 12040000 | 0.009 | 0.029 | 11.1 | 313.1 | 0.04 |
| Antilipemic Agents^ | 24060000 | 0.009 | 0.020 | -38.7 | 133.7 | -0.29 |
| Antidepressants, Miscellaneous^ | 28160492 | 0.008 | 0.013 | -14.7 | 210.9 | -0.07 |
| Analgesics and Antipyretics, Miscellaneous | 28089200 | 0.008 | 0.002 | -5.2 | 138.3 | -0.04 |
| Antimuscarinics^ | 86120400 | 0.008 | 0.015 | -28.5 | 161.3 | -0.18 |
| Central Nervous System Agents, Miscellaneous^ | 28920000 | 0.008 | 0.018 | 2.2 | 272.9 | 0.01 |
| Other Miscellaneous Therapeutic Agents | 92920000 | 0.008 | 0.014 | -29.7 | 200.6 | -0.15 |
| Insulins^ | 68200800 | 0.008 | 0.020 | -4.1 | 177.8 | -0.02 |
| Prostaglandin Analogs^ | 52402800 | 0.008 | 0.011 | -35.3 | 69.1 | -0.51 |
| Anti-inflammatory Agents | 84060000 | 0.007 | 0.003 | -20.3 | 169.5 | -0.12 |
| Quinolones | 8121800 | 0.007 | 0.004 | -4.2 | 102.2 | -0.04 |
| Fibric Acid Derivatives^ | 24060600 | 0.007 | 0.011 | -21.4 | 153.3 | -0.14 |
| Cardiotonic Agents^ | 24040800 | 0.007 | 0.001 | -13.4 | 29.1 | -0.46 |
| Antigout Agents^ | 92160000 | 0.006 | 0.001 | -17.4 | 43.9 | -0.40 |
| Nitrates and Nitrites^ | 24120800 | 0.006 | 0.002 | -4.4 | 113.4 | -0.04 |
| Antineoplastic Agents | 10000000 | 0.006 | 0.037 | 1.5 | 432.1 | 0.00 |
| Hypotensive Agents^ | 24080000 | 0.006 | 0.009 | -31.5 | 225.4 | -0.14 |
| alpha-Adrenergic Blocking Agents^ | 24200000 | 0.006 | 0.001 | -16.7 | 83.8 | -0.20 |
| Tricyclics and Other Norepinephrine-reuptake Inhibitors^ | 28160428 | 0.005 | 0.001 | -15.5 | 70.6 | -0.22 |
| Estrogens^ | 68160400 | 0.005 | 0.006 | -21.8 | 42.9 | -0.51 |
| Antimuscarinics/Antispasmodics | 12080800 | 0.005 | 0.012 | -7.7 | 258.3 | -0.03 |
| Histamine H2-Antagonists^ | 56281200 | 0.005 | 0.001 | -17.4 | 74.0 | -0.23 |
| Mineralocorticoid (Aldosterone) Receptor Antagonists^ | 24322000 | 0.004 | 0.001 | -14.2 | 83.6 | -0.17 |
| 5-alpha-Reductase Inhibitors^ | 92080000 | 0.004 | 0.007 | -28.3 | 174.5 | -0.16 |
| beta-Adrenergic Blocking Agents^ | 52400800 | 0.004 | 0.004 | -36.6 | 140.1 | -0.26 |
| Aminopenicillins | 8121608 | 0.004 | 0.001 | -2.1 | 150.7 | -0.01 |

---------- Table continues in the next page ----------

| Therapeutic class name (1) | AHFS code (2) | Claim share (3) | Spend share (4) | %ΔQ (5) | %ΔOOP (6) | Elasticity (7) |
|---|---|---|---|---|---|---|
| ---------- Table continues from previous page ---------- | | | | | | |
| Atypical Antipsychotics^ | 28160804 | 0.004 | 0.013 | 0.7 | 292.8 | 0.00 |
| Thiazolidinediones^ | 68202800 | 0.004 | 0.016 | 14.3 | 303.6 | 0.05 |
| Skeletal Muscle Relaxants | 12200000 | 0.004 | 0.001 | -9.3 | 91.8 | -0.10 |
| Central alpha-Agonists^ | 24081600 | 0.004 | 0.002 | -12.9 | 124.3 | -0.10 |
| Cyclooxygenase-2 (COX-2) Inhibitors^ | 28080408 | 0.004 | 0.010 | -35.2 | 124.8 | -0.28 |
| Corticosteroids^ | 52080800 | 0.004 | 0.002 | -27.6 | 196.5 | -0.14 |
| Calcium-Channel Blocking Agents^ | 24280000 | 0.004 | 0.002 | -17.3 | 175.5 | -0.10 |
| Leukotriene Modifiers^ | 48102400 | 0.004 | 0.009 | -19.5 | 152.9 | -0.13 |
| First Generation Cephalosporins | 8120604 | 0.003 | 0.001 | -1.6 | 62.4 | -0.03 |
| Antibacterials | 52040400 | 0.003 | 0.003 | -11.4 | 71.7 | -0.16 |
| Anti-inflammatory Agents | 52080000 | 0.003 | 0.004 | -25.3 | 104.4 | -0.24 |
| Estrogen Agonists-Antagonists^ | 68161200 | 0.003 | 0.008 | -55.8 | 151.7 | -0.37 |
| Sulfonamides | 8122000 | 0.003 | 0.001 | -3.2 | 70.0 | -0.05 |
| Serotonin Modulators^ | 28160424 | 0.003 | 0.000 | -8.0 | 46.1 | -0.17 |
| Nonergot-derivative Dopamine Receptor Agonists^ | 28362008 | 0.003 | 0.005 | -11.0 | 282.0 | -0.04 |
| Urinary Anti-infectives | 8360000 | 0.003 | 0.002 | -6.6 | 174.0 | -0.04 |
| Cathartics and Laxatives | 56120000 | 0.003 | 0.001 | -23.1 | 142.9 | -0.16 |
| Tetracyclines | 8122400 | 0.003 | 0.001 | -6.9 | 123.2 | -0.06 |
| Class III Antiarrhythmics^ | 24040420 | 0.003 | 0.003 | -10.3 | 177.4 | -0.06 |
| Antiulcer Agents and Acid Suppressants, Miscellaneous | 56289200 | 0.003 | 0.002 | -17.6 | 195.1 | -0.09 |
| EENT Drugs, Miscellaneous^ | 52920000 | 0.002 | 0.004 | -28.7 | 93.5 | -0.31 |
| Thiazide-like Diuretics^ | 40282400 | 0.002 | 0.001 | -18.5 | 93.3 | -0.20 |
| Antilipemic Agents, Miscellaneous^ | 24069200 | 0.002 | 0.006 | -21.1 | 146.9 | -0.14 |
| Antifungals | 84040800 | 0.002 | 0.001 | -10.7 | 190.2 | -0.06 |
| Dipeptidyl Peptidase-4 (DPP-4) Inhibitors^ | 68200500 | 0.002 | 0.007 | 20.0 | 191.8 | 0.10 |
| Antibacterials | 84040400 | 0.002 | 0.001 | -20.6 | 141.1 | -0.15 |
| Direct Vasodilators^ | 24082000 | 0.002 | 0.001 | -12.9 | 236.5 | -0.05 |
| Antiemetics | 56220000 | 0.002 | 0.000 | -20.9 | 139.8 | -0.15 |
| Nucleosides and Nucleotides^ | 8183200 | 0.002 | 0.003 | -9.2 | 303.6 | -0.03 |
| Skin and Mucous Membrane Agents, Miscellaneous | 84920000 | 0.001 | 0.004 | -40.1 | 183.7 | -0.22 |
| Lincomycins | 8122820 | 0.001 | 0.000 | -8.4 | 144.4 | -0.06 |
| Antiallergic Agents | 52020000 | 0.001 | 0.002 | -36.1 | 102.0 | -0.35 |
| Azoles | 8140800 | 0.001 | 0.001 | 0.1 | 153.4 | 0.00 |
| Nonsteroidal Anti-inflammatory Agents^ | 28080400 | 0.001 | 0.004 | 14.6 | 198.6 | 0.07 |
| Antimalarials^ | 8300800 | 0.001 | 0.001 | -13.4 | 144.5 | -0.09 |
| Nonsteroidal Anti-inflammatory Agents | 52082000 | 0.001 | 0.001 | -19.9 | 60.8 | -0.33 |
| Hydantoins^ | 28121200 | 0.001 | 0.001 | -9.6 | 99.0 | -0.10 |
| Class Ic Antiarrhythmics^ | 24040412 | 0.001 | 0.001 | -27.2 | 342.1 | -0.08 |
| Antidiarrhea Agents^ | 56080000 | 0.001 | 0.000 | -10.9 | 71.8 | -0.15 |
| Antipruritics and Local Anesthetics | 84080000 | 0.001 | 0.003 | -26.8 | 311.1 | -0.09 |
| Prokinetic Agents | 56320000 | 0.001 | 0.000 | -10.5 | 57.6 | -0.18 |
| Carbonic Anhydrase Inhibitors^ | 52401200 | 0.001 | 0.001 | -39.1 | 80.6 | -0.48 |
| Vaccines | 80120000 | 0.001 | 0.002 | -39.6 | 162.1 | -0.24 |
| Protectants^ | 56283200 | 0.001 | 0.001 | -10.4 | 114.5 | -0.09 |
| Penicillins | 8121600 | 0.001 | 0.000 | -17.3 | 64.2 | -0.27 |
| Barbiturates^ | 28120400 | 0.001 | 0.000 | -12.7 | 285.6 | -0.04 |
| Selective alpha-1-Adrenergic Blocking Agents^ | 12160412 | 0.001 | 0.001 | -36.5 | 70.2 | -0.52 |
| Vitamin D^ | 88160000 | 0.001 | 0.000 | -13.5 | 286.4 | -0.05 |
| Azoles | 84040808 | 0.001 | 0.000 | -16.9 | 182.3 | -0.09 |
| Macrolides | 8121200 | 0.001 | 0.000 | 0.4 | 259.3 | 0.00 |
| Disease-modifying Antirheumatic Drugs^ | 92360000 | 0.001 | 0.008 | -17.3 | 184.5 | -0.09 |
| Anti-inflammatory Agents, Miscellaneous^ | 52089200 | 0.001 | 0.002 | -41.8 | 202.6 | -0.21 |
| Respiratory Smooth Muscle Relaxants^ | 86160000 | 0.001 | 0.000 | -1.5 | 96.3 | -0.02 |
| Phenothiazines^ | 28160824 | 0.001 | 0.000 | -3.3 | 114.5 | -0.03 |
| Second Generation Cephalosporins | 8120608 | 0.001 | 0.000 | 0.4 | 208.5 | 0.00 |
| Bile Acid Sequestrants^ | 24060400 | 0.001 | 0.001 | -17.6 | 384.1 | -0.05 |
| Renin Inhibitors^ | 24324000 | 0.001 | 0.001 | -19.2 | 78.0 | -0.25 |
| Anticoagulants | 20120400 | 0.001 | 0.004 | -8.6 | 258.1 | -0.03 |
| Antiprotozoals, Miscellaneous | 8309200 | 0.000 | 0.000 | -7.8 | 92.5 | -0.08 |

^ Classes that are classified as predominantly maintenance classes.

# Table A15: Estimated Elasticities for All "Common" Drugs

| Drug name (1) | Brand/Generic (2) | Claim share (3) | Spend share (4) | %ΔQ (5) | %ΔOOP (6) | Elasticity (7) |
|---|---|---|---|---|---|---|
| All common drugs | - | 0.654 | 0.543 | -11.8 | 249.9 | -0.05 |
| Simvastatin^ | generic | 0.034 | 0.011 | -10.8 | 110.8 | -0.10 |
| Lisinopril^ | generic | 0.028 | 0.005 | -12.6 | 57.3 | -0.22 |
| Atorvastatincalcium^ | brand | 0.022 | 0.055 | -48.3 | 143.3 | -0.34 |
| Levothyroxinesodium^~ | brand | 0.021 | 0.006 | -21.6 | 13.9 | -1.56 |
| Levothyroxinesodium^~ | generic | 0.018 | 0.003 | -13.9 | 38.8 | -0.36 |
| Amlodipinebesylate^ | generic | 0.018 | 0.006 | -17.5 | 123.5 | -0.14 |
| Omeprazole^ | generic | 0.017 | 0.010 | -24.3 | 242.9 | -0.10 |
| Warfarinsodium^ | generic | 0.017 | 0.004 | -19.2 | 82.8 | -0.23 |
| Hydrocodonebitartrateandac | generic | 0.017 | 0.003 | -3.7 | 98.5 | -0.04 |
| Hydrochlorothiazide^* | generic | 0.016 | 0.002 | -20.4 | 38.1 | -0.54 |
| Atenolol^~ | generic | 0.016 | 0.002 | -19.9 | 32.5 | -0.61 |
| Clopidogrelbisulfate^* | brand | 0.015 | 0.047 | 4.8 | 215.4 | 0.02 |
| Metforminhydrochloride^~ | generic | 0.014 | 0.003 | -9.5 | 106.7 | -0.09 |
| Metoprololtartrate^ | generic | 0.014 | 0.001 | -15.8 | 33.2 | -0.48 |
| Furosemide^* | brand | 0.014 | 0.001 | -11.5 | 30.2 | -0.38 |
| Metoprololsuccinate^ | brand | 0.012 | 0.009 | -23.1 | 135.4 | -0.17 |
| Diltiazemhydrochloride^~* | generic | 0.009 | 0.006 | -15.4 | 291.1 | -0.05 |
| Potassiumchloride^ | generic | 0.009 | 0.003 | -13.5 | 168.7 | -0.08 |
| Alendronatesodium^ | generic | 0.009 | 0.003 | -19.8 | 136.4 | -0.15 |
| Valsartan^~ | brand | 0.008 | 0.015 | -32.6 | 89.3 | -0.37 |
| Amlodipinebesylate^~ | brand | 0.008 | 0.004 | -22.3 | 65.2 | -0.34 |
| Rosuvastatincalcium^ | brand | 0.007 | 0.019 | -44.9 | 137.2 | -0.33 |
| Zolpidemtartrate | generic | 0.007 | 0.002 | -11.1 | 95.1 | -0.12 |
| Pravastatinsodium^ | generic | 0.007 | 0.003 | -12.2 | 156.1 | -0.08 |
| Carvedilol^ | generic | 0.007 | 0.002 | -11.1 | 144.4 | -0.08 |
| Triamtereneandhydrochlorot^~* | generic | 0.007 | 0.001 | -19.1 | 43.8 | -0.44 |
| Lisinoprilandhydrochloroth^~ | generic | 0.007 | 0.002 | -7.8 | 89.1 | -0.09 |
| Prednisone | generic | 0.007 | 0.001 | -1.2 | 35.3 | -0.03 |
| Esomeprazolemagnesium^ | brand | 0.006 | 0.023 | -31.9 | 269.8 | -0.12 |
| Donepezilhydrochloride^~ | brand | 0.006 | 0.020 | 19.5 | 362.5 | 0.05 |
| Potassiumchloride^~ | brand | 0.006 | 0.002 | -15.9 | 94.0 | -0.17 |
| Metoprololsuccinate^ | generic | 0.006 | 0.004 | -15.8 | 280.8 | -0.06 |
| Furosemide^* | generic | 0.006 | 0.001 | -11.3 | 52.1 | -0.22 |
| Citalopramhydrobromide^ | generic | 0.006 | 0.001 | -5.6 | 73.3 | -0.08 |
| Lovastatin^~ | generic | 0.005 | 0.002 | -5.3 | 172.0 | -0.03 |
| Escitalopramoxalate^ | brand | 0.005 | 0.009 | -29.1 | 115.3 | -0.25 |
| Digoxin^* | generic | 0.005 | 0.001 | -11.0 | 36.3 | -0.30 |
| Ezetimibe^~ | brand | 0.005 | 0.012 | -34.3 | 128.9 | -0.27 |
| Valsartanandhydrochlorothi^ | brand | 0.005 | 0.011 | -44.1 | 112.6 | -0.39 |
| Tramadolhydrochloride | generic | 0.005 | 0.001 | -9.8 | 83.9 | -0.12 |
| Allopurinol^~* | generic | 0.005 | 0.001 | -17.7 | 28.4 | -0.62 |
| Tamsulosinhydrochloride^ | brand | 0.005 | 0.010 | -36.1 | 192.1 | -0.19 |
| Glipizide^~ | generic | 0.005 | 0.001 | 1.5 | 108.6 | 0.01 |
| Memantinehydrochloride^ | brand | 0.005 | 0.014 | 17.7 | 258.8 | 0.07 |
| Fluticasonepropionateandsa^ | brand | 0.005 | 0.018 | -20.0 | 342.7 | -0.06 |
| Enalaprilmaleate^~ | generic | 0.005 | 0.001 | -14.3 | 73.2 | -0.20 |
| Gabapentin^ | generic | 0.005 | 0.002 | -10.1 | 234.5 | -0.04 |
| Azithromycin* | generic | 0.004 | 0.001 | 2.0 | 148.6 | 0.01 |
| Amoxicillin | generic | 0.004 | 0.000 | -8.3 | 23.1 | -0.36 |
| Pioglitazonehydrochloride^~* | brand | 0.004 | 0.015 | 14.7 | 310.3 | 0.05 |
| Isosorbidemononitrate^* | generic | 0.004 | 0.001 | -1.3 | 106.3 | -0.01 |
| Meloxicam^ | generic | 0.004 | 0.001 | -18.4 | 54.7 | -0.34 |
| Celecoxib^* | brand | 0.004 | 0.010 | -35.2 | 123.2 | -0.29 |
| Glimepiride^ | generic | 0.004 | 0.001 | 3.1 | 86.6 | 0.04 |
| Fluticasonepropionate | generic | 0.004 | 0.002 | -26.9 | 277.7 | -0.10 |

---------- Table continues in the next page ----------

| Drug name (1) | Brand/Generic (2) | Claim share (3) | Spend share (4) | %ΔQ (5) | %ΔOOP (6) | Elasticity (7) |
|---|---|---|---|---|---|---|
| ---------- Table continues from previous page ---------- | | | | | | |
| Paroxetinehydrochloride^ | generic | 0.004 | 0.001 | -16.7 | 177.2 | -0.09 |
| Spironolactone^~* | generic | 0.003 | 0.001 | -14.0 | 79.4 | -0.18 |
| Oxycodonehydrochlorideanda | generic | 0.003 | 0.001 | -4.7 | 254.6 | -0.02 |
| Ramipril^ | generic | 0.003 | 0.002 | -19.8 | 189.9 | -0.10 |
| Montelukastsodium^* | brand | 0.003 | 0.008 | -19.7 | 153.6 | -0.13 |
| Albuterolsulfate^ | brand | 0.003 | 0.002 | -10.4 | 13.4 | -0.78 |
| Tiotropiumbromide^ | brand | 0.003 | 0.012 | -5.4 | 275.2 | -0.02 |
| Insulinglargine^ | brand | 0.003 | 0.009 | -4.0 | 184.2 | -0.02 |
| Amitriptylinehydrochloride^ | generic | 0.003 | 0.000 | -14.5 | 30.4 | -0.48 |
| Cephalexin* | generic | 0.003 | 0.000 | -0.7 | 54.4 | -0.01 |
| Clonidinehydrochloride^ | generic | 0.003 | 0.000 | -14.1 | 52.7 | -0.27 |
| Losartanpotassium^~ | brand | 0.003 | 0.005 | -32.7 | 62.3 | -0.53 |
| Pantoprazolesodium^ | brand | 0.003 | 0.007 | -32.6 | 236.5 | -0.14 |
| Ranitidinehydrochloride^ | generic | 0.003 | 0.001 | -18.7 | 69.2 | -0.27 |
| Trazodonehydrochloride^* | generic | 0.003 | 0.000 | -7.4 | 38.9 | -0.19 |
| Sertralinehydrochloride^* | brand | 0.003 | 0.001 | -10.6 | 91.2 | -0.12 |
| Amlodipinebesylateandbenaz^ | brand | 0.003 | 0.005 | -37.3 | 212.8 | -0.18 |
| Alendronatesodium^~ | brand | 0.003 | 0.005 | -58.2 | 144.9 | -0.40 |
| Sertralinehydrochloride^* | generic | 0.003 | 0.001 | -18.2 | 106.2 | -0.17 |
| Tamsulosinhydrochloride^ | generic | 0.003 | 0.002 | -13.9 | 162.2 | -0.09 |
| Benazeprilhydrochloride^~ | generic | 0.003 | 0.001 | -3.1 | 77.8 | -0.04 |
| Sulfamethoxazoleandtrimeth | generic | 0.003 | 0.000 | -3.1 | 40.3 | -0.08 |
| Fluoxetinehydrochloride^ | generic | 0.003 | 0.001 | -12.8 | 113.5 | -0.11 |
| Finasteride^ | generic | 0.002 | 0.003 | -20.2 | 380.0 | -0.05 |
| Amlodipinebesylateandbenaz^~ | generic | 0.002 | 0.004 | -25.9 | 294.7 | -0.09 |
| Losartanpotassium^~ | generic | 0.002 | 0.001 | 10.8 | 150.8 | 0.07 |
| Irbesartan^~ | brand | 0.002 | 0.004 | -30.0 | 60.4 | -0.50 |
| Mirtazapine^ | generic | 0.002 | 0.001 | -4.2 | 120.8 | -0.03 |
| Cyclobenzaprinehydrochlori | generic | 0.002 | 0.000 | -5.8 | 50.7 | -0.11 |
| Glyburide^~* | generic | 0.002 | 0.001 | -3.7 | 140.5 | -0.03 |
| Warfarinsodium^ | brand | 0.002 | 0.002 | -28.9 | 23.2 | -1.25 |
| Quetiapinefumarate^ | brand | 0.002 | 0.006 | 0.3 | 243.0 | 0.00 |
| Azithromycin | brand | 0.002 | 0.001 | -3.6 | 121.7 | -0.03 |
| Polyethyleneglycol3350 | generic | 0.002 | 0.001 | -26.2 | 224.3 | -0.12 |
| Losartanpotassiumandhydroc^~ | brand | 0.002 | 0.003 | -38.5 | 69.1 | -0.56 |
| Pregabalin^ | brand | 0.002 | 0.005 | -9.5 | 158.3 | -0.06 |
| Naproxen^ | generic | 0.002 | 0.000 | -14.6 | 67.0 | -0.22 |
| Venlafaxinehydrochloride^ | brand | 0.002 | 0.004 | -22.2 | 238.2 | -0.09 |
| Gabapentin^~* | brand | 0.002 | 0.001 | -15.7 | 235.0 | -0.07 |
| Triamtereneandhydrochlorot^~* | brand | 0.002 | 0.000 | -21.7 | 33.7 | -0.64 |
| Sitagliptin^~ | brand | 0.001 | 0.006 | 25.8 | 191.5 | 0.13 |
| Duloxetinehydrochloride^ | brand | 0.001 | 0.004 | -20.9 | 166.5 | -0.13 |
| Digoxin^~* | brand | 0.001 | 0.000 | -22.6 | 10.4 | -2.18 |
| Famotidine^ | generic | 0.001 | 0.000 | -14.2 | 73.1 | -0.19 |
| Ramipril^~ | brand | 0.001 | 0.002 | -28.0 | 98.7 | -0.28 |
| Pantoprazolesodium^ | generic | 0.001 | 0.002 | -23.9 | 292.1 | -0.08 |
| Glipizide^~ | brand | 0.001 | 0.001 | -10.6 | 151.3 | -0.07 |
| Zolpidemtartrate | brand | 0.001 | 0.003 | -26.6 | 217.6 | -0.12 |
| Ciprofloxacinhydrochloride | generic | 0.001 | 0.000 | -12.9 | 48.3 | -0.27 |
| Promethazinehydrochloride | generic | 0.001 | 0.000 | -5.4 | 84.8 | -0.06 |
| Losartanpotassiumandhydroc^~ | generic | 0.001 | 0.001 | -3.2 | 182.9 | -0.02 |
| ---------- Table continues in the next page ---------- | | | | | | |

| Drug name (1) | Brand/Generic (2) | Claim share (3) | Spend share (4) | %ΔQ (5) | %ΔOOP (6) | Elasticity (7) |
|---|---|---|---|---|---|---|
| ---------- Table continues from previous page ---------- | | | | | | |
| Allopurinol^~* | brand | 0.001 | 0.000 | -15.0 | 21.4 | -0.70 |
| Venlafaxinehydrochloride^ | generic | 0.001 | 0.002 | -19.2 | 271.5 | -0.07 |
| Fentanyl* | generic | 0.001 | 0.002 | -8.6 | 323.4 | -0.03 |
| Hydrochlorothiazide^~* | brand | 0.001 | 0.000 | -24.2 | 48.9 | -0.49 |
| Carvedilol^ | brand | 0.001 | 0.002 | -21.1 | 257.4 | -0.08 |
| Glyburide^~* | brand | 0.001 | 0.000 | -0.6 | 98.2 | -0.01 |
| Ibuprofen^ | generic | 0.001 | 0.000 | -10.0 | 30.2 | -0.33 |
| Diltiazemhydrochloride^~ | brand | 0.001 | 0.001 | -21.1 | 224.0 | -0.09 |
| Fluticasonepropionate^ | brand | 0.001 | 0.002 | -35.1 | 201.1 | -0.17 |
| Oxycodonehydrochloride | generic | 0.001 | 0.000 | 0.3 | 220.0 | 0.00 |
| Olanzapine^~ | brand | 0.001 | 0.003 | 17.9 | 414.0 | 0.04 |
| Risperidone^~ | brand | 0.001 | 0.001 | -0.6 | 389.6 | 0.00 |
| Carisoprodol | generic | 0.001 | 0.000 | -4.3 | 66.4 | -0.06 |
| Risperidone^ | generic | 0.001 | 0.001 | -2.1 | 524.5 | 0.00 |
| Levetiracetam^ | generic | 0.000 | 0.001 | 3.8 | 405.3 | 0.01 |
| Divalproexsodium^ | generic | 0.000 | 0.000 | 1.4 | 310.9 | 0.00 |
| Oxycodonehydrochloride | brand | 0.000 | 0.002 | 23.3 | 325.0 | 0.07 |
| Lansoprazole^ | brand | 0.000 | 0.002 | -54.7 | 270.8 | -0.20 |
| Morphinesulfate | generic | 0.000 | 0.000 | -13.4 | 338.6 | -0.04 |
| Spironolactone^~* | brand | 0.000 | 0.000 | -14.4 | 85.6 | -0.17 |
| Lamotrigine^ | generic | 0.000 | 0.000 | -0.8 | 347.9 | 0.00 |
| Divalproexsodium^~ | brand | 0.000 | 0.001 | -10.2 | 224.6 | -0.05 |
| Lansoprazole^ | generic | 0.000 | 0.001 | -36.7 | 117.2 | -0.31 |
| Levetiracetam^~ | brand | 0.000 | 0.001 | 23.3 | 424.3 | 0.05 |
| Albuterolsulfate^ | generic | 0.000 | 0.000 | -18.3 | 160.2 | -0.11 |
| Glimepiride^~ | brand | 0.000 | 0.000 | -14.2 | 79.6 | -0.18 |
| Metforminhydrochloride^~ | brand | 0.000 | 0.000 | 1.5 | 88.1 | 0.02 |
| Lamotrigine^ | brand | 0.000 | 0.001 | 16.6 | 433.1 | 0.04 |
| Isosorbidemononitrate^~* | brand | 0.000 | 0.000 | 2.7 | 167.5 | 0.02 |
| Ciprofloxacinhydrochloride | brand | 0.000 | 0.000 | 2.3 | 95.5 | 0.02 |
| Morphinesulfate | brand | 0.000 | 0.000 | 3.9 | 428.0 | 0.01 |
| Simvastatin^ | brand | 0.000 | 0.000 | -29.1 | 87.5 | -0.33 |
| Pravastatinsodium^~ | brand | 0.000 | 0.000 | -25.5 | 109.4 | -0.23 |
| Atenolol^~ | brand | 0.000 | 0.000 | -33.9 | 29.7 | -1.14 |
| Lovastatin^~ | brand | 0.000 | 0.000 | -38.8 | 183.0 | -0.21 |
| Metoprololtartrate^~ | brand | 0.000 | 0.000 | -17.7 | 46.6 | -0.38 |
| Mirtazapine^~ | brand | 0.000 | 0.000 | 1.9 | 143.8 | 0.01 |
| Fentanyl* | brand | 0.000 | 0.000 | -22.1 | 244.0 | -0.09 |
| Enalaprilmaleate^~ | brand | 0.000 | 0.000 | -47.9 | 98.5 | -0.49 |
| Fluoxetinehydrochloride^~ | brand | 0.000 | 0.000 | 15.5 | 153.6 | 0.10 |
| Lisinopril^~ | brand | 0.000 | 0.000 | -43.7 | 12.4 | -3.52 |
| Finasteride^~ | brand | 0.000 | 0.000 | -10.8 | 59.8 | -0.18 |
| Meloxicam^ | brand | 0.000 | 0.000 | -12.6 | 112.1 | -0.11 |
| Tramadolhydrochloride | brand | 0.000 | 0.000 | -9.6 | 127.9 | -0.08 |
| Benazeprilhydrochloride^~ | brand | 0.000 | 0.000 | -38.4 | 15.1 | -2.54 |
| Citalopramhydrobromide^~ | brand | 0.000 | 0.000 | -51.1 | 72.2 | -0.71 |
| Paroxetinehydrochloride^~ | brand | 0.000 | 0.000 | -54.1 | 22.1 | -2.45 |
| Carisoprodol | brand | 0.000 | 0.000 | -47.1 | 133.7 | -0.35 |
| Clonidinehydrochloride^~ | brand | 0.000 | 0.000 | -6.5 | 57.8 | -0.11 |
| Famotidine^ | brand | 0.000 | 0.000 | 31.5 | 114.3 | 0.28 |
| Ranitidinehydrochloride^ | brand | 0.000 | 0.000 | 51.1 | 148.6 | 0.34 |
| Naproxen^ | brand | 0.000 | 0.000 | -60.6 | 51.8 | -1.17 |
| Cyclobenzaprinehydrochlori | brand | 0.000 | 0.000 | -25.3 | 189.1 | -0.13 |
| Sulfamethoxazoleandtrimeth | brand | 0.000 | 0.000 | 32.4 | 26.6 | 1.22 |

^ Maintenance drug.

~ Chronic drug.

* Drugs that are in the "Lower Substitution" subsample.